IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 18, NO. 8, AUGUST 1996 837

Texture Features tor Browsing and

Retrieval of Image Data

8.8. Manjunathi and W.Y. Ma

Abstract—image content based retrieval is emerging as an important
research area with application to digital libraries and multimedia
databases. The focus of this paper is on the image processing aspects and in particular using texture information for browsing and retrieval of large image data. We propose the use of Gabor wavelet features for texture analysis and provide a comprehensive experimental evaluation. Comparisons with other multiresoiution texture features using the Brodatz texture database indicate that the Gabor features provide the best pattern retrieval accuracy. An application to browsing large air photos is illustrated.

Index Terms—Digital libraries, image database, content-based image retrieval, texture analysis, Gabor wavelets.

+

1 INTRODUCTION

RETRIEVAL of image data based on pictorial queries is an interest» ing and challenging problem. The recent emergence of multimedia databases and digital libraries makes this problem all the more important. While manual image annotations can be used to a cer— tain extent to help image search, the feasibility of such an ap-proach to large databases is a questionable issue. In some cases, such as face or texture patterns, simple textual descriptions can be ambiguous and often inadequate for database search.
The objective of this paper is to study the use of texture as an image feature for pattern retrieval. An image can be considered as a mosaic of different texture regions, and the image features asso— ciated with these regions can be used for search and retrieval. A typical query could be a

region of interest provided by the user,
such as outlining a vegetation patch in a satellite image. The input information in such cases is an intensity pattern or texture within a rectangular window. See Fig. 6 for an example of a texture based browsing application.
Texture analysis has a

long history and texture analysis algo-
rithms range from using random field models to multiresolution filtering techniques such as the wavelet transform. Several re-searchers have considered the use of such texture features for pat-tern retrieval [18], [19]. This paper focuses on a multiresolution representation based on Gabor filters. The use of Gabor filters in extracting textured image features is motivated by various factors. The Gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency [4]. These filters can be considered as orien— tation and scale tunable edge and line (bar) detectors, and the sta-tistics of these microfeatures in a given region are often used to characterize the underlying texture information. Gabor features have been used in several image analysis applications including texture classification and segmentation [1], [14], image recognition [5], [8], [13], image registration, and motion tracking [15].
The main contributions of this paper are summarized below:

1) A simple texture feature representation based on Gabor features is proposed, and a filter design strategy is sug—

º The authors are with the Department ofElectrical and Computer Engineering, University of California at Santa Barbara, Santa Barbara, CA 93106-9560. E—maíl: manj@ccc.ucsb.edu, wei@iplab.ecc.ucsb.eilu.
Manuscript received Dec. 16, 1994. Recommended for acceptance by R. Picard. Por information on obtaining reprints of this article, please send e—mail to: transpami@compurcrbrg, and reference IE EECS Log Number P96055.

gested to reduce the redundancy in the representation.
An adaptive filter selection algorithm is proposed which can facilitate fast image browsing.
A detailed comparison wilh the performance of three other multiscale texture features is provided. Our proposed repre-sentation compares favorably in terms of feature computa-tions and retrieval accuracy.

'

Finally, an application to browsing large air photos is dem-
onstrated.

2V

3v

4v

2 TEXTURE FEATURE EXTRACTION

2.1 Gabor Functions and Wavelets

A two dimensional Gabor function 30:, y) and its Fourier trans-form G(u, U) can be written as:

3(x): ——í— ex —l 3:+y—2 4-2 'Wx (1) ly Znoxay p 2 C72 O_2 ”7,

y

x

G

_

1 (iz—W)2 vz I

2
(um) —

“pl"? —;3—+— l

<>,

where o“:
1/27m'r and ou =1/27roy. Gabor functions form a
complete but nonorthogonal basis set. Expanding a signal using this basis provides a localized frequency description. A class of self—similar functions, referred to as Gabor wavelets in the following discussion, is now considered. Let g(x, y) be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of g(x, y) through the generat— ing function:

gmn(xl y):

ªimG(x" y,)!
x’:
a_m(x cos 9 + ysin 6), and y' =

a'm(—x sine +

y

cos 6), (3)

u > 1, m, n

=

integer

where 9 =

nrc/K and K is the total number of orientations. The
n

scale factor &“

pendent of m.

in (3) is meant to ensure that the energy is inde—

2.2 Gabor Filter Dictionary Design
The nonorthogonality of the Gabor wavelets implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy. Let U, and Uh denote the lower and upper center frequencies of interest. Let K be the
number of orientations and S be the number of scales in the mul—

tiresolution decomposition. Then the design strategy is to ensure that the half—peak magnitude support of the filter responses in the frequency spectrum touch each other as shown in Fig. 1. This re— sults in the following formulas for computing the filter parameters O'“ and o‘v (and thus 0‘)(and cry).

—

u Li S; — (“nuª “(h/ [> '

ºu-W'
I

t

”

In 21

(“ª

21 2

(““fºi T

0', (4) = an) «

n

*

n

——

,

1

2k

L

h

It], u;
where W:

Llh and m:

0, 1, S

—

1. ln order to eliminate sensi—

tivity of the filter response to absolute intensity values, the real (even) components of the 2D Gabor filters are biased by adding a constant to make them zero mean (This can also be done by setting C(O, O) in (2) to zero).

838 IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 18, NO. 8, AUGUST 1996

0.6 «|? | | « x

0.4-

02*

0.1—

——C.1 -

—O.2 . . v I .
70.6 "0.4 70.2 D 0.2 0.4 0.6

Fig. 1. The contours indicate the half-peak magnitude of the filter re— sponses in the Gabor filter dictionary. The filter parameters used are U,,:

0.4, U,= 0.05, K: 6, and S: 4.

2.3 Feature Representation

Given an image 10:, y), its Gabor wavelet transform is then defined
to be

Ian(x,y):II(x1, yl)gmn*(x T

xl'y T

y1)dx1dyl, (5)
where *
indicates the complex conjugate. It is assumed that the
local texture regions are spatially homogeneous, and the mean ,umw and the standard deviation (TW of the magnitude of the trans— form coefficients are used to represent the region for classification and retrieval purposes:

[JW:
JHWmÁxyNdxdy, and UW:

J'I(|W,,m(x,le —

,um"? dxdy. (6)

A feature vector is now constructed using um and om" as fea— ture components. In the experiments, we use four scales S:4 and
six orientations K =
6, resulting in a feature vector

,? =

[H00 ºoo “01 ”35 GssI‘ (7)

2.3. 1 Distance Measure:

Consider two image patterns 1 and j, and let tº) and fº) represent the corresponding feature vectors. Then the distance between the two patterns in the feature space is defined to be

d(i,j) =

Zãdmutidl
where

(í) (Í) (Í) Ii)
. . 'umrl T

Iumrz O—rrm —

o-mn

: __ —_-— 8 drirlz(1’]) a(umn) a(cmn)

()

Mum) and a(omn) are the standard deviations of the respective features over the entire database, and are used to normalize the individual feature components.

2.4 Retrieval Performance
2.4.1 Texture Database

The texture database used in the experiments consists of 116 dif— ferent texture classes. Each of the 512 >< 512 images is divided into 16 128 >< 128 nonoverlapping subimages, thus creating a database of 1,856 texture images. A query pattern in the following is any one of the 1,856 patterns in the database. This pattern is then proc-essed to compute the feature vector as in (7). The distance d(i, j), where i is the query pattern and j

is a pattern from the database, is
computed. The distances are then sorted in increasing order and the closest set of patterns are then retrieved. In the ideal case all

the top 15 retrievals are from the same large image. The perform— ance is measured in terms of the average retrieval rate which is defined as the average percentage number of patterns belonging to the same image as the query pattern in the top 15 matches.
We observe that the use of cm” feature in addition to the mean

improves the retrieval performance considerably. This perhaps explains the low classification rate of the Gabor filters reported in [3] where only the mean value was used. On the average 74.37% of the correct patterns are in the top 15 retrieved images. The per— formance increases to 92% if the top 100 (about 6% of the entire database) retrievals are considered instead (i.e., more than 13 of the 15 correct patterns are present). Some retrieval examples are shown in Fig. 2. A detailed comparison with other texture features is given in Section 4.

Fig. 2. Texture browsing using Gabor features. Examples shown are some of the difficult patterns to analyze. The average retrieval rate is shown in the parentheses: (a) Texture browsing interface with all 116 textures and retrievals for D42, lace (50%), (b) D43, swinging light bulb (54%), (c) D23, beach pebbles (54%), and (d) D91, clouds (25%). The first image in each of (b)-(d) represents the query image. Note that some of the incorrect matches actually look quite similar to the query pattern.

3 ADAPTIVE FILTER SELECTION

In many cases it is desirable to reduce the image processing time to the extent possible while not seriously affecting the overall per— formance. One way to reduce the computations is to select the Gabor filters in a pattern dependent way.

IEEE TRANSACTIONS ON PATI'ERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 18,

An insight into the discrimination quality of individual features
can be obtained by considering the average intraclass to inter—class
distance ratio for each of the components. This ratio is about 0.25
on the average, with higher frequency components providing a
better discrimination [16]. in database search one is often inter-
ested in finding out how much of the search space can be elimi-nated by using a particular feature. Suppose we want to keep all the 15 correct textures belonging to the same pattern in the set of retrieved images. The average threshold is about 30%, and as in the previous case, high frequency components have a better dis— crimination. More details can be found in [16]. These experiments indicate that each feature component can individually provide useful discrimination measure which can be further improved by selectively choosing these filters based on the query pattern.
The selection scheme described here uses the spectral informa-tion in conjunction with the average database image properties to select a subset of filters. The purpose is to identify salient query image properties which best distinguish it from the database items. Fig. 3 shows a schematic diagram of this method. The dif— ference between the spectrum of the input image pattern and the average spectrum provides information about salient spectral characteristics of the given image. Let

D(a,v) =[13mm,(u,v)i— il—mm(u, v)]r/(Fw(u,v)),
(11,17) is the Fourier transform of the input image pat— Where EMD“! tern. F111m” (14,0) and FCHT (u, v) are the mean and variance associated

with the distribution of Fourier transforms of allimage patternsin the database. D(u, v) basically is the energy of the difference nor-malized by the variance associated with each frequency compo— nent (a, a). Each filter is evaluated based on the total difference en-ergy within its spectral coverage:

n

:

Z2 D(% U).

IGmn(a, y)|2 r

where Gmn(u,v) is the frequency response of the filter gm(x,y). The larger the value gm is, the better the performance of the filter will be for pattern retrieval. Thus the filters can be ordered based on cm“. Fig. 3 shows an example where the input pattern has strong orientation preference which distinguishes the pattern from much of the database images. Using only the top four filters, one
can retrieve on the average about 50% of the correct patterns in the
top 15 retrieved patterns [16]. Such a

strategy may be reasonable in
many image database applications and amounts to a significant savings in image processing computations. Fig. 4 shows some examples wherein different number of filters are used. Computing the entire Gabor feature vector of (7) takes 9.3 sec— onds of CPU time (in MATLAB on a SUN—SpacmO, see Table 2). Search and retrieval takes about 1.02 seconds. Using only four feature components requires 2.3 seconds of feature extraction time including the adaptive filter selection (0.7 seconds), and about 0.1
seconds for search and retrieval.

4 EXPERIMENTAL RESULTS

A detailed comparison with some of the other recently proposed multiresolution texture image features are made in this section. For the Gabor feature case, the 24 >< 2 component feature vectors are used. An application to browsing large airrphotos is illustrated.

4.1 Comparison with Other Texture Features

The comparisons are made with the conventional pyramid— structured wavelet transform (PWT) features, tree-structured wavelet transform (TWT) features, and the multiresolution simul-taneous autoregressive model (MR-BAR) features. The filter coeffi— cients used for computing PWT are the 16—tap Daubechies or—

NO. 8, AUGUST 1996 839

#1 #3

#2 #4

selected filters

database

diflerence

measure

Input FFT
pattern

Fig. 3. An example of the filter selection strategy.

flv
[ªº I I I]—_mW E

llI

Lmis Emªl l“:—__

|:~wriu:m1srs 1quEl- mm: mmm:

m.;;- mms

' “

mw :::m reu.

' —

m.» "Em.“ was—.08

Fig. 4. Examples of retrieval using a different number of filters selected by the adaptive filter selection strategy. The upper-left image in each block is the query image (D83: woven matting), and the top 15 matches are shown in row scan order with increasing distance. Top: Results using one filter; bottom: results using two filters. With four fil-ters, all the correct 15 patterns are retrieved for this case.

thogonal wavelets [6] (same as the ones used in [3] for the TWT). The 128 >< 128 image pattern is decomposed into three levels (4 >< 3
= 12 bands) of the wavelet transform. The mean and standard de-

viation of the energy distribution corresponding to each of the subbands at each decomposition level are used to construct a (12 >< 2)
feature vector.

In [3], decomposition of image subbands at each level is based on energy considerations and this results in a tree structured dev composition where different patterns have different structures. For pattern retrieval applications, it is convenient to have a fixed structure. A fixed decomposition tree can be obtained by sequene tially decomposing the LL, LH, and. HL subbands. The HH band is not decomposed as this often does not lead to stable features. A three level decomposition results in 52 (4(1 + 3 + 9)) subbands. As in the PWT, the mean and standard deviation in each subband are

used to construct a 52 >< 2 component feature vector.
The third set of feature used are the MR—SAR model features

[17]. Previous work [9], [20] indicate that the MR—SAR features at levels 2, 3, and 4, provide the best overall performance. At each level, five parameters are computed to represent the texture, thus requiring a total of 15 feature components. The Mahalanobis dis-tance is used to compare the feature vectors.

4.1.1 Summary of Comparisons
Table 1 provides a

summary of the experimental results. it shows
the retrieval accuracy of the different texture features for each of the 116 texture classes in the database. The Gabor features give the best performance at close to 74% retrieval. This is closely followed by the MR-SAR features at 73%. The TWT features perform mar—

840

THE D* LABELS INDICATE TEXTURES FROM THE BORDATZ ALBUM [2] AND 0* LABELS INDICATE TEXTURES FROM THE USC DATABASE.

TABLE 1
AVERAGE RECOGNITION RATE FOR THE 116 TEXTURE IMAGES IN THE DATABASE.

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. ‘18, NO. 8, AUGUST 1996

CPU TIMES (ON A SUN SPARCZO WITH ONE PROCESSOR) AND FEATURE VECTOR LENGTH FOR THE VARIOUS TEXTURE FEATURES.
GABOR FEATURES ARE COMPUTED IN MATLAB AND ALL THE OTHERS ARE WRITTEN IN C LANGUAGE.

Gabor Features
. PWT TWT MRÉAR
Adaptive

“

Full feature

(4 filters)

Feature Extractlon 9.3 sec. 2.3 sec 1.3 sec 2.3 sec 34.0 sec
Time

Feature Vector 48 8 24 104 15

Length (24 x 2) (4 x 2) (12 X 2) (52 x 2)

Searching and 1.02 sec 0.1 sec 0.98 sec 1.70 sec 0.70 sec
Sorting Time

Average Retrieval Rate % Average Retrieval Rate% Average Retrieval Rate%

Gabor PWT TWT MRSAH Gabor PWT TWT MRSAR Gabor PWT TWT MRSAFI
D1 99.17 97.08 97.50 98.75 D42 50.00 59.17 56.67 38.75 D81 100.00 90.83 9583 9417
D2 5292 32.50 36.75 67.92 013 11.75 13.75 11.25 9.58 D82 100.00 100.00 100.00 100.00
D3 94.58 75.42 58.33 49.17 D44 1250 13.33 12.92 15.00 D83 100.00 98.75 99.58 9917
D4 100.03 90.83 67.92 88.33 D45 14.58 22.08 25.83 3.33 D84 100.00 100.00 100.00 99.58
D5 72.92 52.92 52.08 63.33 D46 9417 70.42 80.42 92.50 D85 99.58 96.67 100.00 99.17
D6 100.00 100.00 100.60 100.00 D47 100.00 100.00 100.00 9750 D86 91.67 60.83 71.67 95.00
D7 35.42 21.25 19.58 52.08 D48 49.17 72.08 77.08 86.67 D87 99.58 92.08 82.92 9292
D8 9500 79.58 7458 95.42 D49 100.00 100.00 100.00 100.00 D88 41.67 48.75 51.67 45.83
D9 93 75 8458 77 50 6458 D50 87.92 56.25 75.83 87.08 D89 2125 22.08 26.75 10.00
D10 8583 78.75 68.75 79.17 D51 83.75 91.25 93.33 90.83 D90 34 58 19.58 31 67 47.08
D11 100.00 73.75 80.00 9833 D52 72.08 55.12 61.25 70.00 D91 25.42 12.92 16.25 2750
D12 8625 79.58 70.42 7500 D53 100.00 100.00 100.00 100.00 D92 87.50 92.50 92.08 68.33
D13 4292 38.75 30.83 43.75 D54 5083 56.67 47.50 5792 D93 72.92 38.75 30.00 6208
014 100.00 100.00 100.07 100.00 D55 100.00 97.08 99.17 100.00 D94 100.00 91.67 92.08 90.83
D15 6917 79.58 57.92 80.00 056 100.00 103.00 100.00 100.00 D95 8750 65.00 92.50 8750
D16 100.00 100.00 100.00 100.00 957 100.00 94.17 100.00 100.00 D96 98.33 77.50 94.17 99.17
D17 100.00 100.00 100.00 100.00 D58 29.58 18.33 25.42 2792 D97 37.08 29.17 39.58 37.92
1318 79.17 79. 17 92.50 69.58 D59 20.42 10.83 14.17 23.33 D98 5250 52.08 65.00 7292
D19 80.42 73.33 62.50 86.67 D60 5250 30.00 37.92 50.00 D100 87.08 71.67 53.33 74.58
D20 100.00 87.50 94.58 100.00 D61 43.75 47.92 45.83 41.25 13101 58.75 65.00 63.75 6292
D21 100.00 100.00 100.00 100.00 D62 35.83 45.00 50.83 43.75 13102 53.33 51.25 51.25 56.25
D22 75.00 8250 70.83 56.67 D63 34.17 24.17 27.08 35.00 13103 56.67 72.50 73.75 6667
D23 53.75 41.25 41.67 39.58 D64 94.58 90.00 79.17 97.92 13104 54.58 59.17 66.67 4875
D24 215.83 95.83 82.92 9000 065 100.00 100.00 98.75 100.00 0105 63.33 50.00 44.58 5333
D25 88.75 53 75 48.33 75.83 D66 96.67 90.00 95.00 68.33 D106 44.17 55.83 54.58 51.67
D26 100.00 88.75 99.17 100.00 D67 7000 53.75 6375 62.08 D107 52.50 59.58 60.83 5542
D27 36.67 34.58 34.58 40.42 D68 100.00 99.58 10000 100.00 D108 37.50 28.75 29.58 32.92
D28 95.42 86.67 97.50 88.75 D69 42.50 39.17 44.17 36.25 D109 78.75 73.75 76.67 76.25
D29 7208 60.00 64.58 6750 D70 49.17 45.42 57.50 7917 D110 87.92 78.75 75.42 62.92
1930 33.75 23.75 33.75 5042 D71 42 9'7 45.83 68.75 72.50 0111 90.83 90.42 62.92 9167
D33 7797. 72.50 57.50 9250 D72 47.50 48.75 75 83 79.17 0112 61.67 50.42 58.33 63.33
D34 99.17 92.92 98.33 10000 D73 66.67 51.67 5792 5708 m 100.00 100.00 100.00 92.08
D35 98.33 82.92 68.33 89.17 D74 78.75 85.00 8500 94.58 02 100.00 100.00 98.75 100.00
D36 4917 57.08 30.00 31.67 D75 95.42 86.67 93 75 98.75 03 98.75 75.42 93.33 97.50
D37 100.00 78.75 79.58 99.58 D76 99.17 96.5 95.83 92.08 04 100.00 100.00 100.00 100.00
D38 4667 31.67 29.17 42.08 D77 100.00 100.00 100.09 100.00 05 86.25 83.33 100.00 93.33
D39 39.58 24.17 27.92 60.00 D78 97.50 93.33 85.42 88.33 06 100.00 100.00 100.00 100.00
D40 52.08 56.67 67.50 41.67 D79 100.00 100.00 100.00 97.92 07 71.25 68.75 52.08 57.50
D41 78.75 68.33 52.08 58.33 D80 100.00 85.83 85.83 91.67 Avg. 74.37 68.70 69.41 73.18

TABLE 2

ginally better (694%) than the PWT features (68,7%). Fig. 5 shows
a graph illustrating this retrieval performance as a function of number of top matches considered. ln summary,

' In general, feature components corresponding to higher fre-quencies have better discriminating performance. However, decomposing the HH band in the tree-structured represen— tation often leads to a decrease in performance, indicating
that these features are not Very robust.

Experiments with different wavelet transforms indicate very little variation in performance with respect to the choice of filters [10].

The marginal improvement of the TWT features comes at the expense of having a much larger feature vector, which adds to the overhead associated with indexing and search.

It is important to explore different similarity measures for each of the different sets of features. For example, using the
Mahalanobis distance instead of the Euclidean distance im—

proved the performance from 64% to 73% for the MR—SAR
features. Normalized Euclidean distance worked better for
all the others.

For Brodatz images, best results using the Gabor features were obtained using four scales and six orientations within each
scale. Note that rotation and scale invariance is not addressed.

Table 2 provides the CPU times for feature extraction and se-quential search of the database. The computations involving Ga— bor features are performed in MATLAB where as the other feature computations are implemented in C language. In terms of feature computation time, the MR-SAR is the most expensive.

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 18, NO. 8, AUGUST 1996 841

95 !

' * * '

! !

ggº,

A

, .ar/‘d’,

,

“

,

m

,

_ ,

A _

:
__ ,

*

'

. .

,

& ,

,

,

"

'

. ,,

% f 7....

"

% 85 ' —

o

U7
0)
E
0180 ..
.ª.-
>

. º ,

ã solid: Gabor features

E 75 dotted PWT leatuies :

-

g

dashed: 'FWT features

m

.

e
,?.

g dashdot: MRSAP. model
Ti’ 70- , ., ,... , _

65 T l T T l T T T
20 3C 40 50 80 70 80 90 100

Number 01 top matches considered

Fig. 5. Retrieval performance according to the number of top matches
considered.

4.2 An Image Browsing Example

Query based on texture properties will have many applications in image and multimedia databases. Here, we describe with an ex-ample our current work on incorporating these features for browsing large satellite images and air photos. This work relates to the UCSB Alexandria digital library project [21] whose goal is to create a digital library of spatially indexed data such as maps and satellite images. Typical images in such a database range from few megabytes to hundreds of megabytes, posing challenging prob-lems in image analysis and visualization of data. Content based retrieval will be very useful in this context in answering queries such as “Retrieve all LANDSAT images of Santa Barbara which have less than 20% cloud cover,” or "Find a vegetation patch that looks like this region.”
We are currently investigating the use of texture primitives to ac-complish rapid content based browsing Within an image or across similar images. Fig. 6 shows an example of browsing 5,248 >< 5,248 air photos. The original image is analyzed in blocks 128 >< 128 pix— els and the texture features are computed and stored as image ”meta—data.” The user can select any position and use that pattern to search for similar looking regions. Our current work is on incorpo— rating simple texture based segmentation schemes into this browse ing thus allowing arbitrarily shaped regions into the analysis.

4.3 Discussions

A Gabor wavelet based texture analysis scheme is proposed and its application to image databases is demonstrated. A comprehen-sive performance evaluation of the method is given using a

large
number of textures and a comparison with some of the well known multiresolution texture classification algorithms is made. Further, a novel adaptive filter selection strategy is suggested to reduce the image processing computations while maintaining a reasonable level of retrieval performance. The experimental results indicate that these Gabor feature are quite robust. Rotation and scale invariance is important in many applications and our pre-liminary results on rotation invariant classification [7] using Gabor features are very encouraging.
Finally, a note on similarity measures. It is widely acknowledged that this is an important but a difficult problem. Our initial results using simple hybrid neural network learning algorithms appear very promising in the context of learning similarity [11], [12].

ACKNOWLEDGMENTS

This research was partially supported by National Science Foun— dation grant lRl-9411330 and by NASA under grant number

(b) (c) (d)

Fig. 6. An example of browsing a large air photo using Gabor texture features. Part (a) shows the down-sampled version of the image and the retrieval results on a vegetation pattern, (b) the query pattern con— tains a part of the highway and retrievals are all from highway seg-ments, (0) shows the region containing some buildings (center of the image toward the left), (d) shows one interesting result where the query contains a number marked on the image (lower left corner), and the top matches also contain similar patterns.

NAGW—3951. We thank Professor Picard and F. Liu at MIT for

providing the software for the MR-SAR features and C. Fischer at UCSB for the air photos.

REFERENCES

[1] A.C. Bovic, M. Clark, and W5. Geisler, ”Multichannel Texture
Analysis Using Localized Spatial Fillers," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no, 1, pp. 55-73, Jan. 1990.
[2] P. Brodatz, Textures: A Photographic Album for Artists & Designers.
New York: Dover, 1966.

[3] T. Chang and (É.-C.]. Kuo, “Texture Analysis and Classification
with Tree—Structured Wavelet Transform,” IEEE Trans. Image Processing, vol. 2, no. 4, pp. 429—441, Oct. 1993.
[4]].G. Daugman, ”Complete Discrete 2D Gabor Transforms by Neu-ral Networks for Image Analysis and Compression,” IEEE Trans. ASSP, vol. 36, pp. 1,169—1,179, July 1988.
[5] LC. Daugman, ”High Confidence Visual Recognition of Persons
by a Test of Statistical Independence,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, no. 11, pp. 1,148—1,161, Nov. 1993.
[6] l. Daubechies, ”The Wavelet Transform, Time—Frequency Localiza-
tion and Signal Analysis,” [EEE Trans. Information Theory, vol. 36, pp. 9614,005, Sept. 1990.
[7] G.M. Haley and BS. Manjunath, ”Rotation Invariant Texture
Classification Using the Modified Gabor Filters,” Proc. IEEE ICIP ’95, vol. I, pp. 262-265, Washington D.C., Oct. 1995.

842 IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 18, NO. 8, AUGUST 1996

[8] M. Lades et al., ”Distortion Invariant Object Recognition in the
Dynamic Link Architecture,” IEEE Trans. Computers, vol. 42, no. 3,
pp. Boº—311, Mar. 1993.
[9] F. Liu and R.W. Picard, ”Periodicity, Directionality, and Random?
ness: Wold Features for Image Modeling and Retrieval," MIT
Media Lab Technical Report no. 320, Mar. 1995.
[10] W.Y. Ma and BS. Manjunath, "A Comparison of Wavelet Fea-tures for Texture Annotation,” Proc. IEEE Int'l Conf. Image Proc— essing ’95, vol. II, pp. 256-259, Washington D.C., Oct. 1995.
[11] W.Y. Ma and BS. Manjunath, “Image Indexing Using a Texture Dictionary,” Proc. SPIE, vol. 2,606, pp. 288-296, Philadelphia, Oct.
1995.

[12] W.Y. Ma and BS. Manjunaih, “Texture Features and Learning Similarity,” Proc. IEEE Conf. Computer Vision and Pattern Recognir tion, San Francisco, June 1996.

[13] BS. Manjunath and R. Cliellappa, “A Feature Based Approach to Face Recognition,” Proc. IEEE Conf. CVPR ’92, pp. 373—378, Cham— paign, Ill., June 1992.
[14] B.B. Manjunath and R. Chellappa, "A Unified Approach to Boundary Detection,” IEEE Trans. Neural Networks, vol. 4, no. 1, pp. 96-108, Jan. 1993.
[15] BS. Manjunath, C. Shekhar, and R. Chellappa, “A New Approach to Image Feature Detection with Applications,” Pattern Recognif lion, Apr. 1996.
[16] BS. Manjunath and W.Y. Ma, ”Texture Features for Browsing and Retrieval of Image Data,” CIPR TR 95—06, July 1995 (available on WWW at http:/ /vivaldi.ece.ucsb.edu).
[17]]. Mao and A. Jain, "Texture Classification and Segmentation Using Multiresolution Simultaneous Autoregressive Models,” Pattern Recognition]., vol. 25, no. 2, pp. 173—188, 1992.
[18] W. Niblack et al., ”The QBIC Project," Proc. SPIE, vol. 1,908, pp. 173-181, Feb. 1993.
[19] A. Pentlancl, R.W. Picard, and S. Sclaroff, “Photobook: Tools for Content Based Manipulation of Image Databases,” Proc. ICASSP ’93, vol. V, pp. 161—164, Minneapolis, Apr. 1993.
[20] R.W. Picard, T. Kabir, and F. Liu, ”Real—Time Recognition with the Entire Brodatz Texture Database,” Proc. [EEE Conf. CVPR ’93, pp. 638-639, New York, June 1993.
[21] The Alexandria Digital Library Project, http://alexandria.sdc.ucsb.edu.

Retrieving Multispectral Satellite Images

Using Physics—Based Invariant

Representations

Glenn Healey and Amit Jain

Abstract—We present a set ot algorithms and a search strategy for the robust content—based retrieval of multispectral satellite images. Since the property of interest in these images is usually the physical characteristics of ground cover, we use representations and methods that are invariant to illumination and atmospheric conditions. The representations and algorithms are derived for this application from a physical model for the formation of multispectral satellite images. The
use of several representations and algorithms is necessaw to interpret
the diversity of physical and geometric structure in these images. Algorithms are used that exploit multispectral distributions, multispectral spatial structure, and labeled classes. The performance of the system is demonstrated on a large set of multispectral satellite images taken over different areas of the United States under different illumination and atmospheric conditions.

Index Terms—Image database,image retrieval, color constancy, satellite images, color, machine vision. texture, computer vision, recognition.

+

1 INTRODUCTION

MULTiSFECTRAt. remote—sensing data are being used for an in-creasing number of applications in a diverse set of fields including agriculture, geology, mapping, water resources, and environ—
mental science. The volume of satellite data that is available for

such applications is staggering. A Landsat thematic mapper, for example, generates seven band. images using three visible and four infrared regions of the spectrum. Even though the Landsat pro— vides coarser spatial resolution than many other remote—sensing satellites, a single image corresponding to a 170 km by 185 km region of earth requires over 200 Mbytes of storage and the satel— lite generates about 5,000 images per week. It has been predicted that in a few years the amount of data originating from remote— sensing satellites will reach a

terabyte per day [2].
Given this large volume of data, effective tools for image access are essential to allow the information in the database to be fully exploited. Image database systems traditionally access images using keywords or text associated with the images. Unfortunately, it is often difficult to assign textual descriptions to images and consequently text—based queries often fail. In addition, the task of manually annotating the current volume of satellite imagery
would involve a
large amount of time and expense.
A recent trend in retrieval from image databases has been to allow queries based on image content [12], [11], [15], [1]. Using this paradigm, a user can specify a search using image properties such
as shape, color, or texture. In most cases, the user will not specify
numerical values of these properties, but rather will present the system with example images. The system will compute features from the example and use these features for database indexing. In most cases, a metric is defined on these features that is intended to

model perceptual similarity.

o The authors are with the Department of Electrical and Computer Engi— neering, University of California, Irvine, CA 92717.
E-mail: {healcy, amit}@ece.iici.edu.

Manuscript received [lily 5, 1995.
Recommended for acceptance by R.W. Picard.
For information on obtaining reprints of this article, please send e—mail to: transpami@compater.org, and reference IEEECS Log Number P96052.

0162-8828/96$05.00 ©1996 IEEE