Urban area analysis using Statistics for SAR Imagery report

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1 Data select

```
The urban_area image in this report is select from
Fig. 3.4, in which we choose subimage of 100 pixels * 100 pixels
in urban area and show as Figure 1. In this experiment,
we only select raw intensity HH bands as our objective. So the
codes is very simple and understandable.
> #The road of raw intensity HH bands#
> imagepath <- "/home/a421-2/wenzheng/Report-Statistics-SAR-master
 /Data/Images/ESAR/"
> HH_Complex <- myread.ENVI(paste(imagepath,
                                "ESAR97HH.DAT", sep = ""),
                                 paste(imagepath, "ESAR97HH.hdr", sep = ""))
> HH_Intensity <- (Mod(HH_Complex))^2
> #The area of selected#
> urban_area <- HH_Intensity[1100:1199,1100:1199]
> vexample <- data.frame(HH=as.vector(urban_area))
> plot(imagematrix(equalize(urban_area)))
> imagematrixPNG(name = "./urban_area.png", imagematrix(equalize(urban_area)))
> vexample <- data.frame(HH=as.vector(urban_area))
> summary(vexample)
HH
Min.
1st Qu.:
           16028
Median:
           51070
Mean
          193548
3rd Qu.:
```

181281

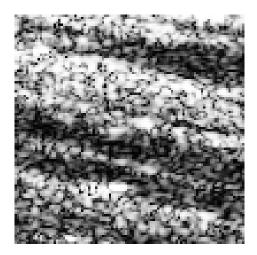


Figure 1: selected area

2 Analysis of Histogram

```
Consider the real part of the HH band of Figure 2 and Figure 3 whose histogram is the top leftmost. assume it is stored in the |HH\_Complex| variable. These data are clearly not uniformly distributed.
```

We will randomly sample (fixing the pseudorandom number generator and the seed for reproducibility) one hundred observations, and then proceed to build its empirical function.

```
>binwidth_complete <-2*IQR(vexample$HH)*length(vexample$HH)^(-1/3)
```

>ggsave(filename = "./HistogramExample.pdf")

```
> binwidth_complete [1] 15340.79
```

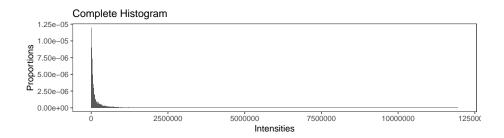


Figure 2: HistogramExample

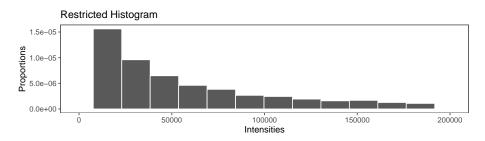


Figure 3: HistogramRestrictedExample

3 The result of estimation

The maximum likelihood estimation is used to evaluate the experimental data. Here we use only one function to achieve this function, and eventually we get a result value.

```
## Estimation require(maxLik)
```

3

```
}
estim.urban_area <- GIO.Estimator.mlm2(urban_area, 1)
LogLikelihoodLknown <- function(params) {
                          p_alpha < -abs(params[1])
                          p_gamma <- abs(params[2])
                          p_L \leftarrow abs(params[3])
                          n \leftarrow length(z)
return (
n*(lgamma(p_L-p_alpha) - p_alpha*log(p_gamma) - lgamma(-p_alpha)) +
                 (p_alpha-p_L)*sum(log(p_gamma + z*p_L))
}
estim.exampleML <- maxNR(LogLikelihoodLknown,
start=c(estim.urban_area$alpha, estim.urban_area$gamma,1),
activePar=c(TRUE,TRUE,FALSE)) $estimate [1:2]
values:
binwidth\_complete : 15340.7948389499
estim.exampleME : num [1:2] -42741 143335
mean: 1
N : 15
sigma2 : 1
> GIO. Estimator.mlm2
function(z, L) {
m1 \leftarrow mean(z)
m2 \leftarrow mean(z^2)
m212 <- m2/m1^2
a < -2 - (L+1) / (L * m212)
g \leftarrow m1 * (2 + (L+1) / (L * m212))
return(list("alpha"=a, "gamma"=g))
<bytecode: 0x5566609e2b40>
> estim.urban_area
$alpha
[1] -2.279272
```

\$gamma [1] 441148

 $> {
m estim.exampleML}$

 $[1] -42740.89 \ 143335.12$

results all above