NUS
National University
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Hand Pose

Huang
School

Introduction

Hand pose recognition plays an important ro
interaction. Its challenge lies in the complexi
and the variety of poses that hands can mak
which mainly focus on 2D input images, igno
information about 3D hand objects and are u
occlusions. We take advantage of the recent
cameras and propose an approach to estima
hand images. It has been demonstrated to b
achieve 70 percent of accuracy.

Estimation with Rand

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n

le in human-computer
ty of hand articulations
ke. Traditional methods
re a lot of critical
unable to deal with self
t advances in depth
ate poses from depth
be efficient and can

1. Our accuracy is XX
2. What are the type o
   example, images w
   little noise? Some s
3. What factors reduce
   a. For some image
      eg)
   b.
4. Efficiency? Compu

dom Forest

ng He

gapore

Results

%

of images which have high accuracy? For

ith no self occlusion? Images which have

specific features are easier to detect?

es our accuracy?

s, hand patches cannot be detected (insert

tation time in each step?

Methods

Our approach consists of three steps:

1. **Hand patch detection**. We began with d
in a given depth image. Pixels outside th
as background and respective values are
the furthest distance from camera.

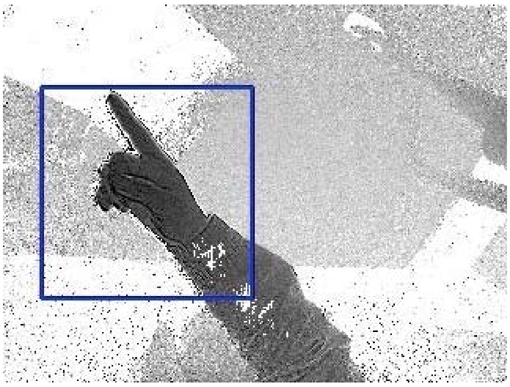


Figure 1: Raw depth image

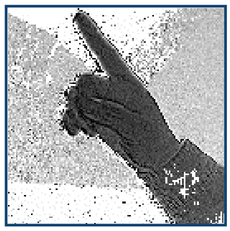


Figure 2: Intermediary step - cropped image

Fi
ha

1. **Feature extraction.** Next, depth features
each image. The mapping *d(x)* is the dep
location *x*. 2D vectors *u, v* are random of

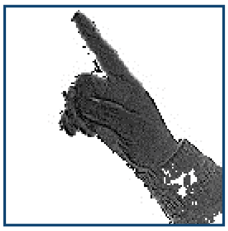
$$f_I(x) = d_I\left(x + \frac{u}{d_I(x)}\right) - d_I\left(x +\right.$$

For each training image, 50 randomly ch
combinations of predefined random *u*, *v*
of 2500x10.

3. **Classification by random forest**.

Recognizing Hand Gestures through M

letecting hand patches
e contour are regarded
e set to 255, indicating



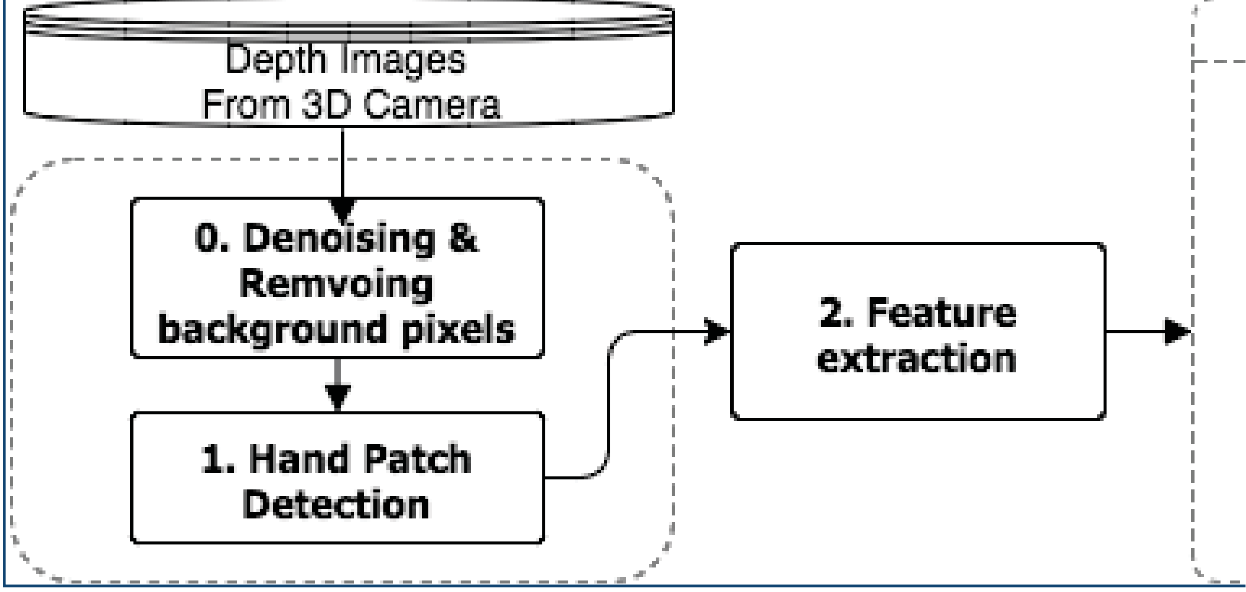
gure 3: Final detected
and patch

s were extracted for
oth value of the pixel
fset positions from *x*.

$$\frac{v}{d_I(x)}\Big).$$

osen pixels and 10
render a feature matrix

Machine Learning



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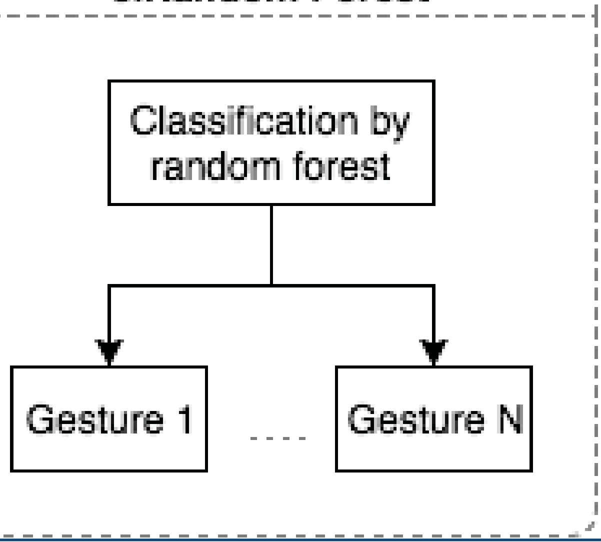
3.Random Forest



We propose an integra
patches from single de
random forest. Future
images whose hand pa

his guidance throughout
data set.

References

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images. Multimedia Tools and A

Conclusion

...ted approach which can detect hand
...pth images and estimate its pose by
...development can be automatically removing
...atch is not detectable.

...nd pose estimation from a single depth image. In: ICCV (2013)
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...Applications (2014), 1–16