**Doctoral Dissertation** 

# A Study on Radar Signal Processing and Object Segmentation for Drone System Applications

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# A Study on Radar Signal Processing and Object Segmentation for Drone System Applications

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## GLOSSARY

AEE	Average Euclidean Error
AMPD	Automatic Multiscale-based Peak Detection
CFAR	Constant False Alarm Rate
CFD	Crack Forest Dataset
CLAHE	Contrast Limited Adaptive Histogram Equalization
CNNs	Convolutional Neural Networks
CPU	Central Processing Unit
DCNN	Deep Convolutional Neural Networks
DLL	Delay-Locked Loop
DNN	Deep Neural Network
FFA	Free-Form Anisotropy
FCN	Fully Convolutional Network
FFT	Fast Fourier Transform
FMCW	Frequency-Modulated Continuous-Wave
FN	False Negative
FP	False Positive
GMM	Gaussian Mixture Model
GPS	Global Positioning System
GUI	Graphical User Interface
IALM	Inexact Augmented Lagrange Multipliers
ІоТ	Internet of Things
IR-UWB	Impulse Radio – Ultra Wideband
ISM	Industry-Science-Medical
LBP	Local Binary Pattern