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Automatic aircraft recognition and identification

Jijoong Kim
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AUTOMATIC AIRCRAFT RECOGNITION AND IDENTIFICATION

by

JIJOONG KIM

B.Eng. (Hons) (The University of Adelaide) 1993

M.Eng.Sc. (The University of Adelaide) 1995

School of Electrical, Computer and Telecommunications Engineering

A thesis submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

from

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August, 2005

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Certification

I, Jijoong Kim, declare that this thesis, submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Signature of Author

Date

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Abstract

Aircraft recognition remains a challenging problem despite a great deal of effort to automate the recognition process. The majority of the aircraft recognition methods assume the successful isolation of the aircraft silhouette from the background, and only a few have actually addressed real world concerns, such as occlusion, clutter and shadows. This thesis presents an automatic aircraft recognition system, which shows improved performance with complex images. This system assumes from the start that the image could possibly be degraded, contain occlusions, clutter, camouflage, shadows and blurring. It is designed to tolerate and overcome the degradations at various analysis stages. The first part of the thesis focuses on the *generic aircraft recognition* problem using a generic description of aircraft parts and the geometric relationships that exist among them. The system implements line groupings in a hierarchical fashion, progressively leading towards a generic aircraft structure. A voting scheme is used to consolidate line groupings belonging to an aircraft while discouraging the formation of spurious line groupings. The aircraft *identification* process is carried out in the second part of the thesis, where the generically recognised aircraft is matched to model candidates. Model matching is carried out via pixel-level silhouette boundary matching. The system is tested on numerous real aircraft, scaled-down model aircraft and non-aircraft images with adverse image conditions. The developed system achieves a recognition rate of 84% at a false alarm rate of 7% on real aircraft images, and an correct matching rate of about 90% and a false matching rate of 7% on the generically recognised aircraft from model aircraft images.

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