



Cairo University

LEARNING-BASED FEATURE SUPER-RESOLUTION FOR LOW-RESOLUTION IMAGE CLASSIFICATION

By

Asaad Musaed Ahmed Anam

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Biomedical Engineering and Systems

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Title of Thesis:

Learning-based Feature Super-resolution for Low-resolution Image Classification

Key Words:

Image resolution; feature learning; partial least-square regression; coupled dictionary learning; material classification.

Summary:

The classification of images from their visual texture has many applications ranging from medical diagnosis applications to image retrieval and object recognition. As image resolution determines the amount of details an image holds, it plays an important role when using digital images for classification tasks. The problem we address in this thesis is one of automatically classifying textural images with low resolution conditions since high resolution images are not always available. In this work, we propose learning-based approaches to infer high-resolution features from low-resolution features extracted from low-resolution images. Applying these learned maps is equivalent to super-resolution (SR) in the feature domain. Two different applications are studied in this work. Experimental and statistical evaluations show significant improvement in classification performance due to applying the proposed techniques in comparison with direct classification in the low-resolution space.

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Dedication

This thesis is dedicated to my brother *Ghamdan Anam* for his continued support and encouragement.

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List of Abbreviations

ANAs	Antinuclear Autoantibodies
CAD	Computer-Aided Diagnosis Systems
CCA	Canonical Correlation Analysis
CDC	Center for Disease Control and Prevention in Atlanta, Georgia, USA
CDL	Coupled Dictionary Learning
CoALBP	Co-occurrence of Adjacent Local Binary Patterns
CUReT	Columbia University Reflection and Transmission Database
GRI	Globally Rotation Invariant
HEp-2	Human Epithelium Larynx Carcinoma (HEp-2) Substrate
HR	High-Resolution
ICIP	International Conference on Image Processing
ICPR	International Conference on Pattern Recognition
IIF	Indirect Immunofluorescence Test
KTH-TIPS	Royal Institute of Technology university Textures under varying Illumination, Pose and Scale dataset
LR	low-Resolution
LS	Large Scales
MCLBP	Multi-scale Co-occurrence Local Binary Pattern
MS	Medium Scales
NIPALS	Non-linear Iterative Partial Least Squares
PLS	Partial Least Squares Regression
QCQP	Quadratically Constrained Quadratic Program
RBF	Radial-Basis Function
RIC-LBP	Rotation Invariant Co-occurrence among Local Binary Patterns
SR	Super-Resolution
SS	Small Scales
SVM	Support Vector Machine Classifier