RANDOMIZED INTRACLASS-DISTANCE MINIMIZING BINARY CODES FOR FACE RECOGNITION

Hao Zhang
Ross Beveridge
Quanyi Mo
Bruce Draper
Jonathon Phillips
Problem Statement

Learn a binary code for each face image, such that …

- Image pairs of the same person have small Hamming distances
- Image pairs of different persons have large Hamming distances

Thousands of bits in practice

100101 100111 001000
Advantages

- Efficient storage
  - Bit values compared to floating values

- Fast distance computation
  - Hamming distance

- Fast query for large scale datasets
  - Explore a Hamming ball
  - No exhaustive search required
State-of-the-art method: **DBC**

bit inconsistency within the same person

\[
\arg\min_{\omega, \xi} \sum_{c \in 1:C} \sum_{m, n \in c} d(b_m, b_n) - \lambda_1 \\
+ \gamma \|\omega\|^2 + \lambda_2 \sum_{k \in 1:N} \xi_k
\]

SVM-style classifier

bit inconsistency between different persons

\[
\sum_{c' \in 1:C} \sum_{p \in c'} \sum_{c'' \in 1:C, c' \neq c''} d(b_p, b_q)
\]

**DBC**: M. Rastegari et al. *Attribute Discovery via Predictable Discriminative Binary Codes*. ECCV 2012
Our Approach: RIDMBC

- Given training data of $C$ persons, learn a binary classifier $\omega$ such that:

$$\arg\min_{\omega} \sum_{c=1}^{C} \sum_{i,j \in c} \|b_i - b_j\| + \gamma \|\omega\|^2 + \lambda \sum_{k=1}^{N} \xi_k$$

- bit inconsistency within the same person
- SVM-style classifier

**RIDMBC:** Randomized Intraclass-Distance Minimizing Binary Codes
Learning One Bit (Classifier)

- Divide images into 2 subject-disjoint sets, $S_1$ and $S_2$
- **Randomly** assign a desired binary label to each person
- Iterate until convergence
  - Train an SVM on $S_1$ and test on $S_2$
  - Change desired labels in $S_2$
  - Swap $S_1$ and $S_2$
Learning One Bit

- Divide images into 2 subject-disjoint sets, $S_1$ and $S_2$
- Randomly assign a desired binary label to each person
- Iterate until convergence
  - Train an SVM on $S_1$ and test on $S_2$
  - Change desired labels in $S_2$ (next slide)
  - Swap $S_1$ and $S_2$
Change Desired Labels in $S_2$

Adjust so each person receives the label associated with the majority.

(a) Before Label Change
(b) After Label Change
Generating Multiple Bits

Loop as many times as desired!

- Divide images into 2 subject-disjoint sets, $S_1$ and $S_2$
- Randomly assign a desired binary label to each person
- Iterate until convergence
  - Train an SVM on $S_1$ and test on $S_2$
  - Change desired labels in $S_2$
  - Swap $S_1$ and $S_2$
Visualizing RIDMBC in 2D

Synthetic 2D data, actual RIDMBC output

8 decision planes: 8-bit binary code
Experiments – The Data

- Labeled Faces in the Wild (LFW)
- Point-and-Shoot Challenge (PaSC)

LFW:

PaSC:
Experiments – Features

- **Gray**: Gray-scale pixel values

- **LBPr1**: Local Binary Pattern (LBP), with a sampling step of 8 and a radius of 1

- **LBPr2**: Local Binary Pattern (LBP), with a sampling step of 8 and a radius of 2
Experiments – Training & Test

- Build the algorithm once
  - LFW View 1 Training Set
  - (3,443 images, 2,132 people).

- This trained algorithm tested on two datasets
  - LFW View 1 Test Set
  - PaSC
    - Cross Dataset Training / Test
RIDMBC vs. DBC on LFW View 1

Classification result on View 1 test set (LBPr1)
Performance on PaSC

RIDMBC vs. DBC

![Graph showing verification rate vs. false accept rate for RIDMBC and DBC methods. The graph compares the performance of RIDMBC and DBC methods in terms of verification rate as the false accept rate varies.]
Performance on PaSC

RIDMBC vs. LRPCA & CohortLDA

P. J. Phillips et al. An Introduction To The Good, the Bad, & the Ugly Face Recognition Challenge Problem, FG’11
Y. Lui et al. Preliminary Studies On The Good, the Bad, And the Ugly Face Recognition Challenge Problem, CVPRW’12
Thank you!
Independence of Binary Coders

Test data: 1000 image pairs
Each binary coder yields 1000 bits: 101…011

Normalized histogram showing highly uncorrelated binary coders
Performance on PaSC

RIDMBC vs. PittPatt

![Graph showing verification rate vs. false accept rate]

- **RIDMBC**
- **PittPatt**

- Axes:
  - Y-axis: Verification Rate
  - X-axis: False Accept Rate
Motivation

- Learn binary classifiers that satisfy
  - They separate all images into two partitions
  - They classify images of the same person in the same partition