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Weighted Multi-scale Local Binary Pattern Histograms for Face Recognition

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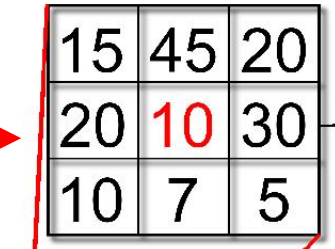
Project: Multimodal biometric technology for safe and easy person authentication 2DP/2.1.1.1.0/APIA/VIAA/098

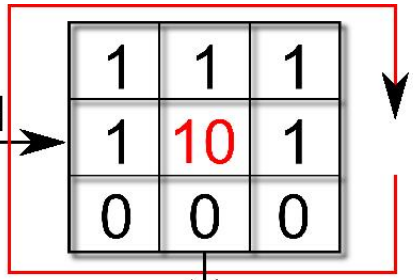
Weighted Multi-scale Local Binary Pattern Histograms for Face Recognition

LBP – Local Binary Patterns

3 x 3 Neighborhood from input image



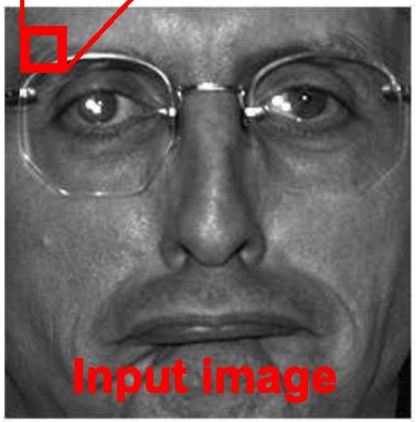
Threshold

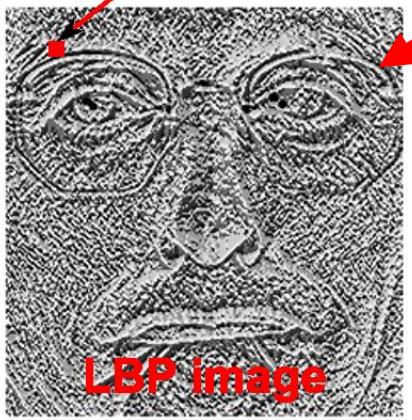


LBP label binary value: 11110001

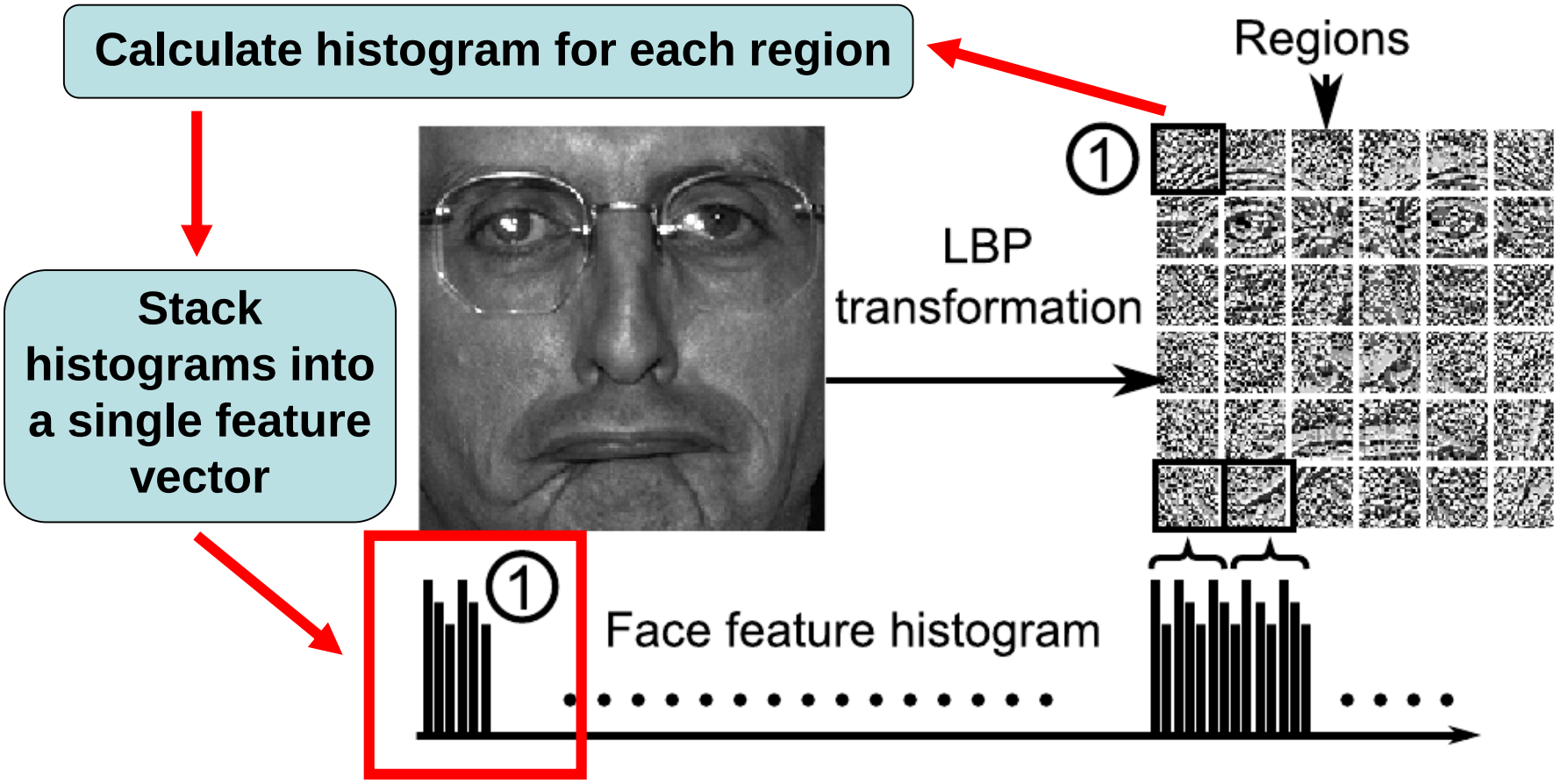
LBP label decimal value: 241

Result of LBP transformation





Weighted Multi-scale Local Binary Pattern Histograms for Face Recognition



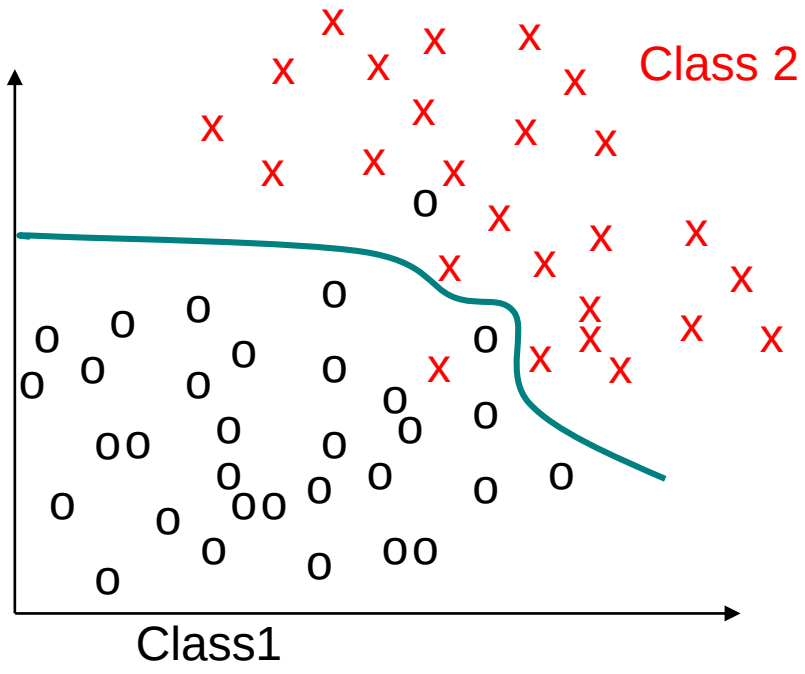
Weighted Multi-scale Local Binary Pattern Histograms for Face Recognition

Recognition stage:

- **compare LBP histogram of the input image with histograms from the database**
- **nearest neighbor classifier (NNC) is used (Example: Euclidean distance)**

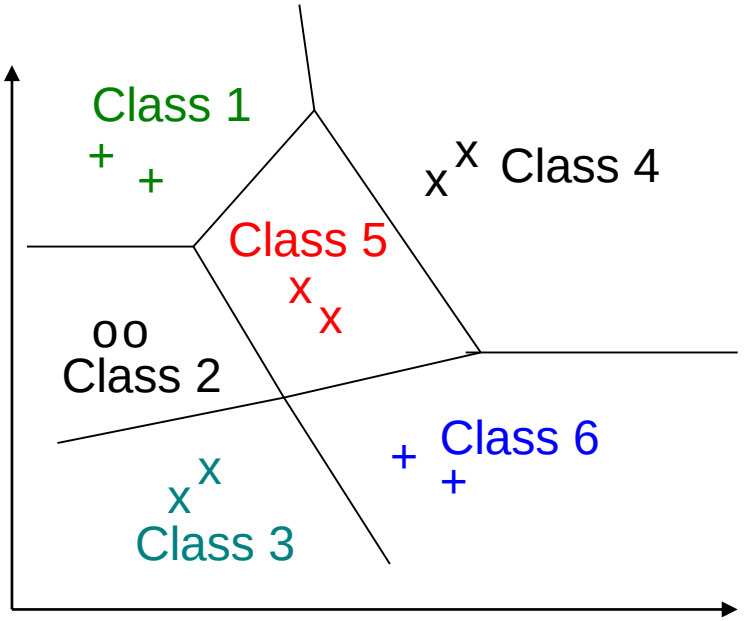
Recognition stage

2 class classification problem
(for example, face detection)



- ANN, SVM can be used
- Lot's of training data for each class
- Number of classes not high

Face recognition task



- not enough data for ANN, SVM (!)
- few training samples per class
- Number of classes is high(1000 FERET)
- Nearest Neighbour Classifier is usually used

Is Nearest Neighbor Classifier (NNC) the best solution?

Why NNC is usually used? Problem:

- Having plenty of classes / persons
- Only a few training examples per class / person

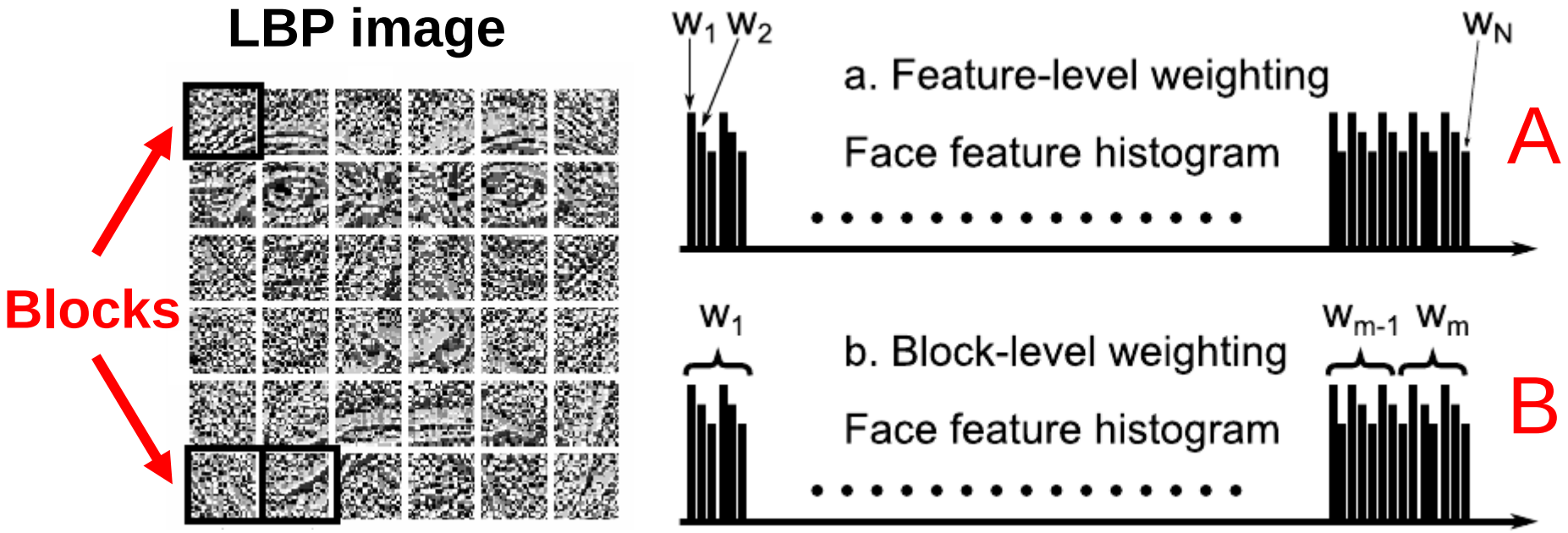
~~**Artificial Neural Networks**~~
~~**Support Vector Machines**~~
~~**...**~~

Possible improvement

Weighted Nearest Neighbor Classifier (WNNC)
Utilize statistical information from all classes

A Mini-Batch Discriminative Feature Weighting Algorithm

Proposed in two levels: feature and block weighting:



Presented approach amplifies the features/blocks, which are more relevant for the recognition by adjusting the weights.

Weights are determined in the learning process.

A Mini-Batch Discriminative Feature Weighting Algorithm

Only TWO training examples per class are needed (Photo 1 & 2)

d – Euclidean distance between weighted histograms		Person 1	Person 2	Person 3…	Person M
		Photo 2	Photo 2	Photo 2	Photo 2
Person 1	Photo 1				
Person 2	Photo 1				
Person 3…	Photo 1				
Person M	Photo 1				

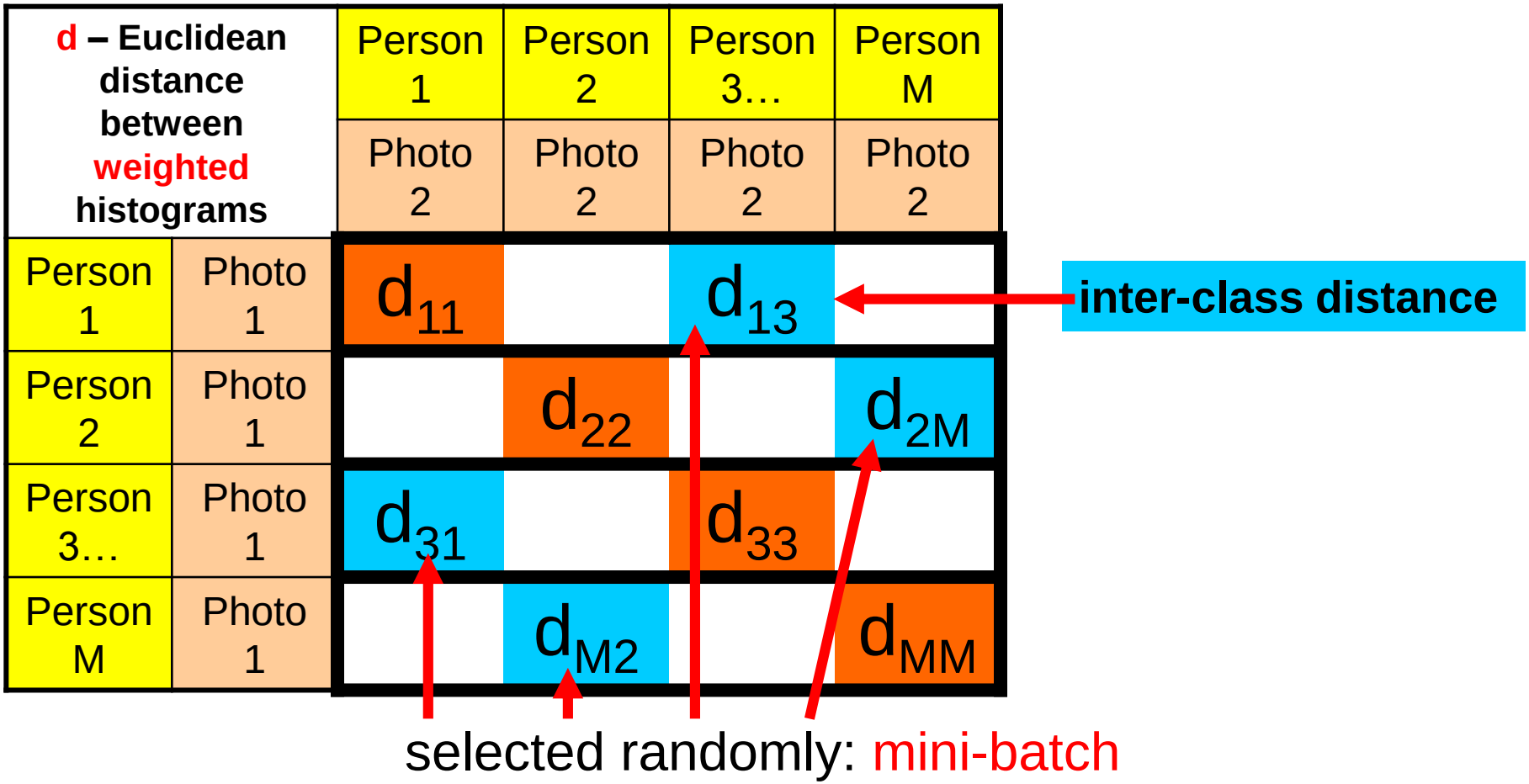
A Mini-Batch Discriminative Feature Weighting Algorithm

Only two training examples per class are needed (Photo 1 & 2)

d – Euclidean distance between weighted histograms		Person 1	Person 2	Person 3…	Person M
		Photo 2	Photo 2	Photo 2	Photo 2
Person 1	Photo 1	d_{11} ← **intra-class distance**			
Person 2	Photo 1		d_{22}		
Person 3…	Photo 1			d_{33}	
Person M	Photo 1				d_{MM}

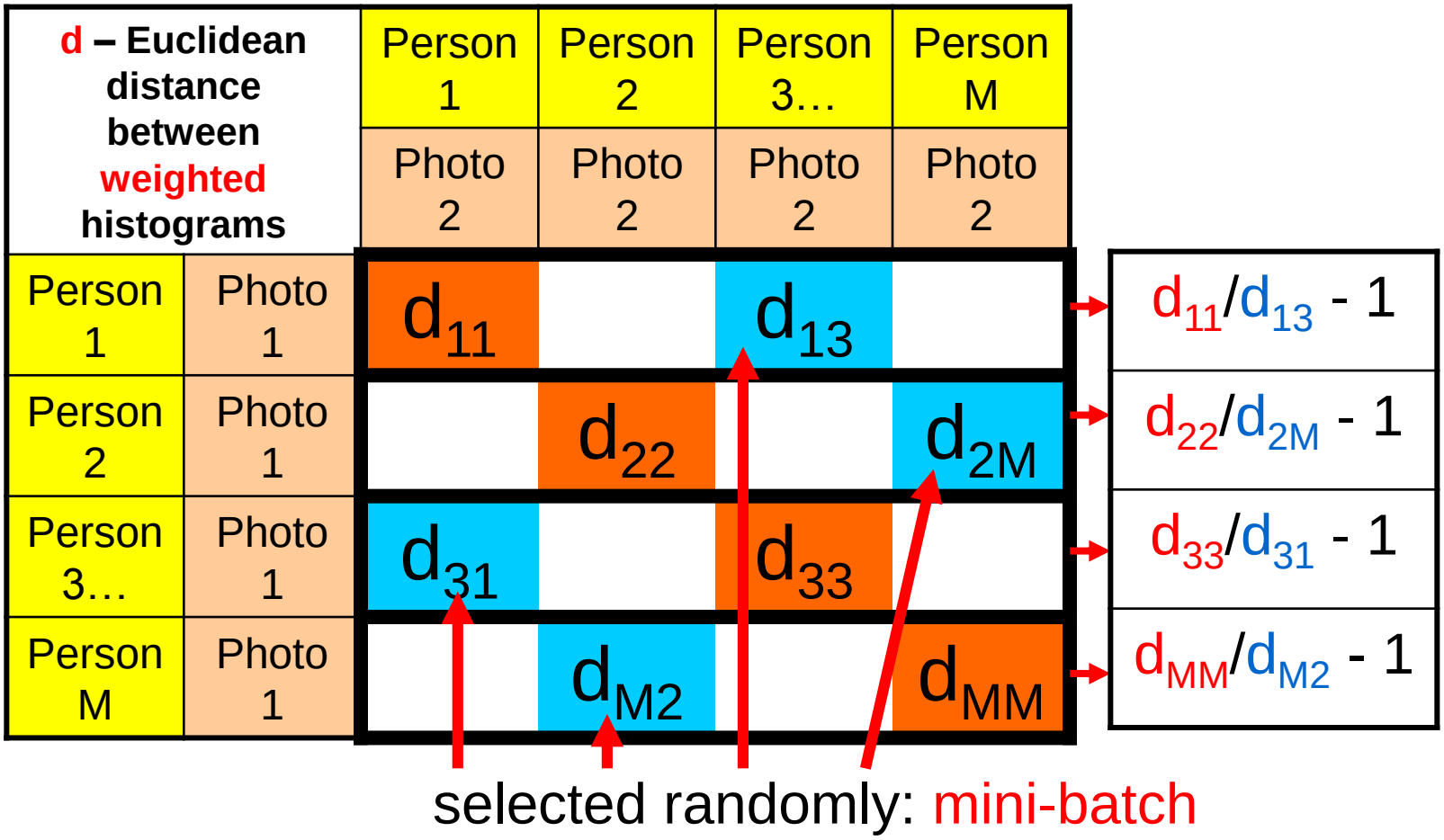
A Mini-Batch Discriminative Feature Weighting Algorithm

Only two training examples per class are needed (Photo 1 & 2)



A Mini-Batch Discriminative Feature Weighting Algorithm

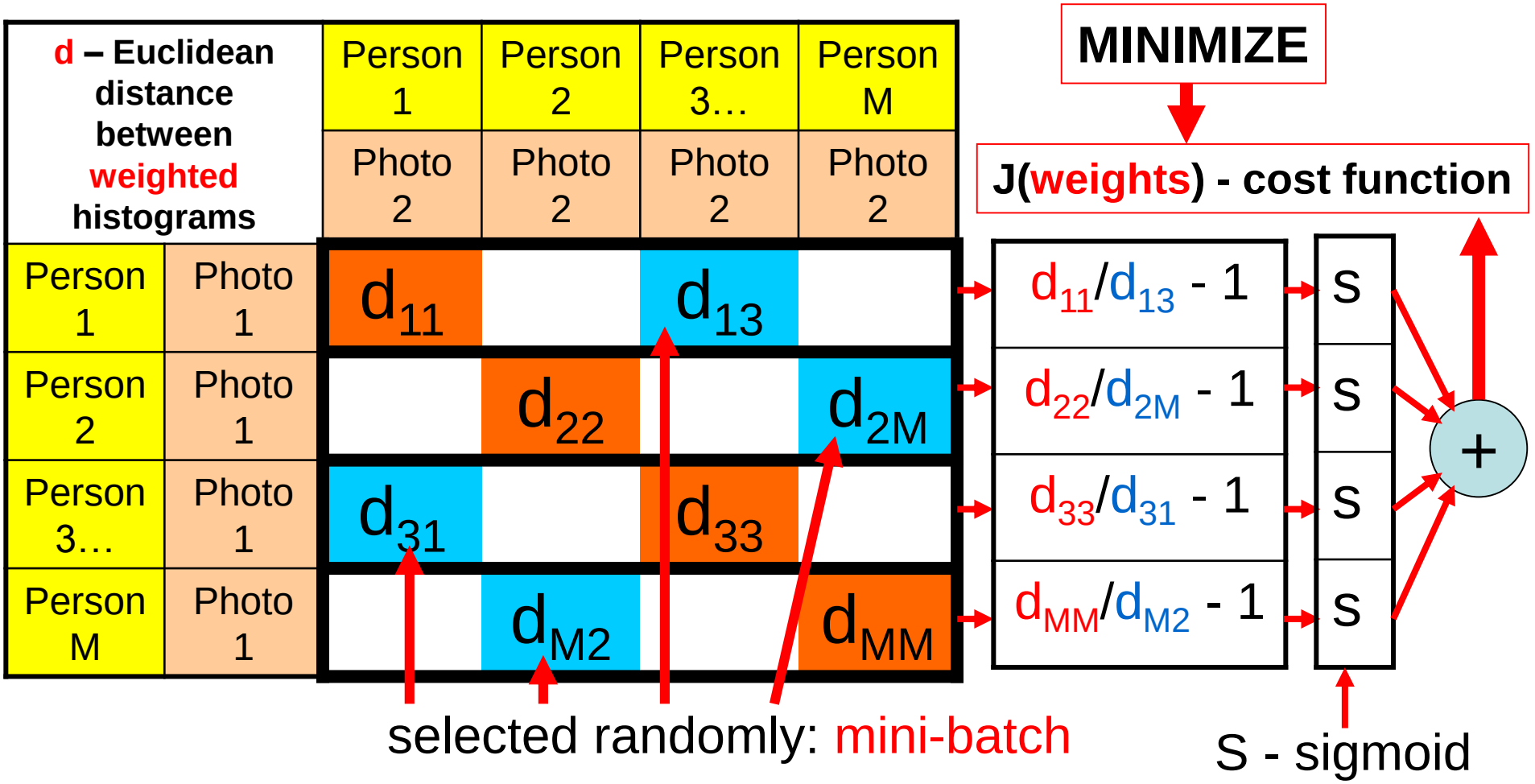
Only two training examples per class are needed (Photo 1 & 2)



selected randomly: mini-batch

A Mini-Batch Discriminative Feature Weighting Algorithm

Only two training examples per class are needed (Photo 1 & 2)



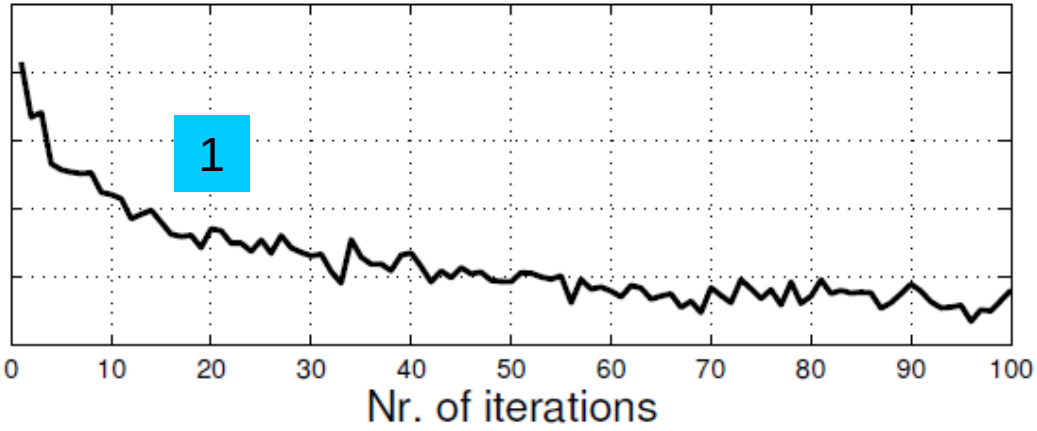
A Mini-Batch Discriminative Feature Weighting Algorithm

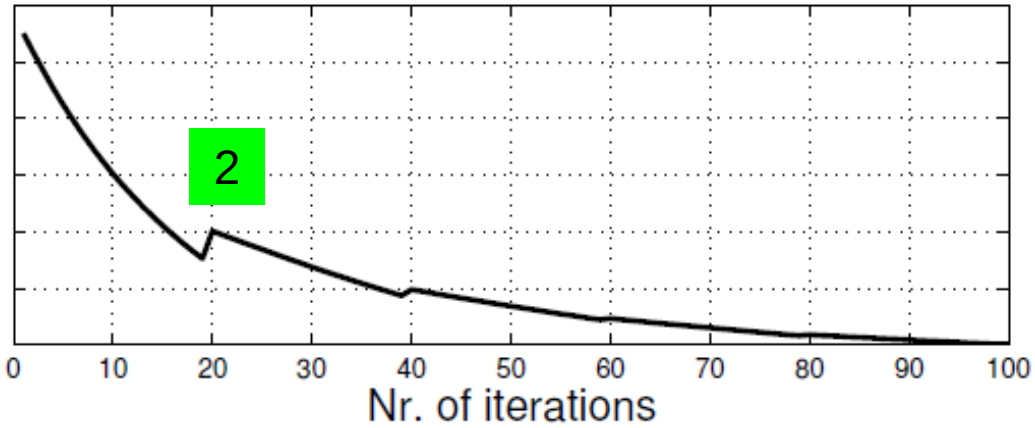
d – Euclidean distance between weighted histograms		Person 1	Person 2	Person 3…	Person M
		Photo 2	Photo 2	Photo 2	Photo 2
Person 1	Photo 1	d_{11}		d_{13}	d_{1M}
Person 2	Photo 1		d_{22}	d_{23}	d_{2M}
Person 3…	Photo 1	d_{31}	d_{32}	d_{33}	
Person M	Photo 1		d_{M2}	d_{M3}	d_{MM}

Learning data selection:

1. Selected randomly at each iteration
2. Select smallest inter-class distances for all persons after each N iterations

A Mini-Batch Discriminative Feature Weighting Algorithm





Learning data selection:

1 Selected randomly at each iteration

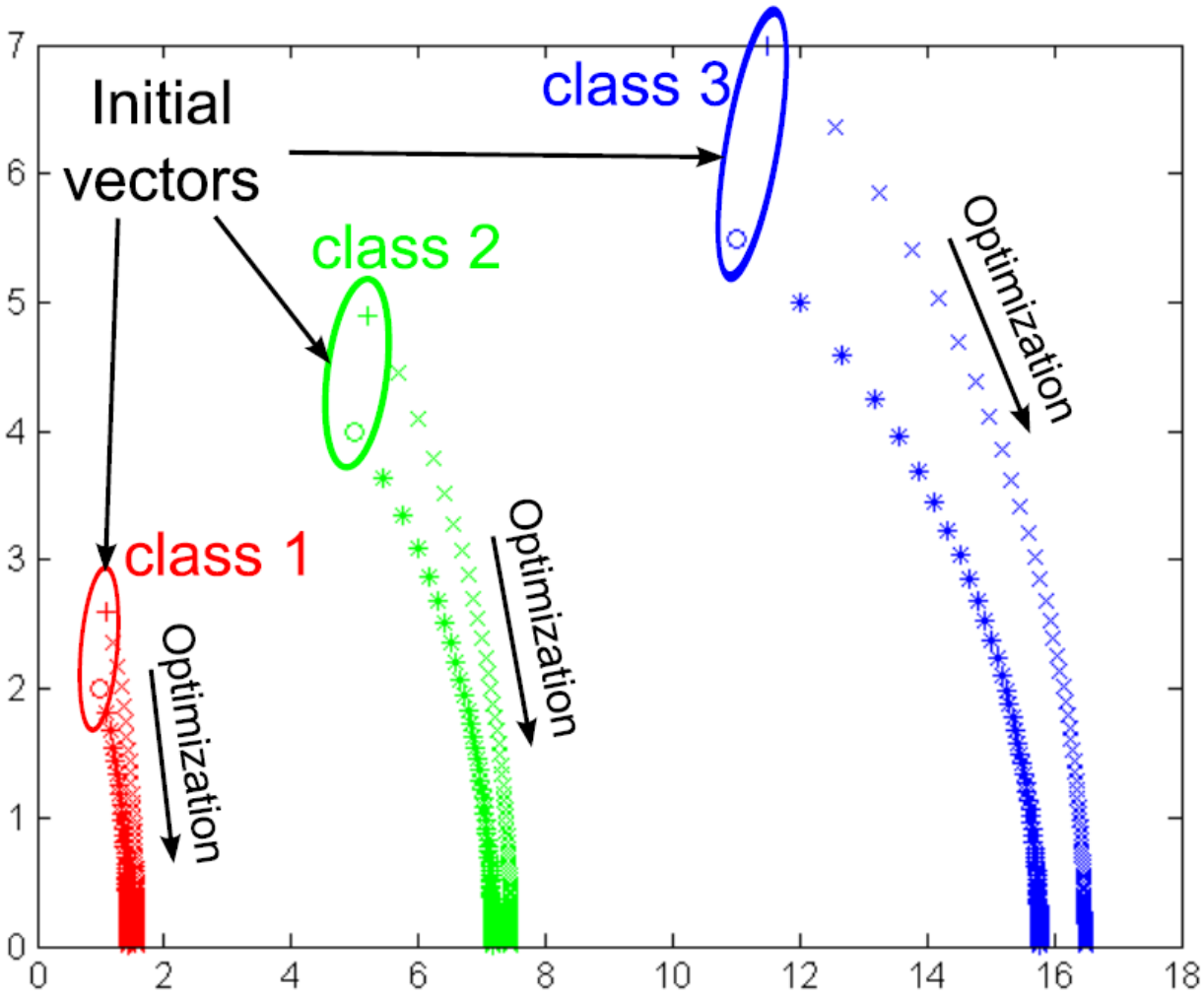
2 Select smallest inter-class distances for all persons after each N=20 iterations

A Mini-Batch Discriminative Feature Weighting Algorithm

Each face is described with N=16384 LBT parameters.

Lets simplify the task:

Lets consider that each face (class) is described with 2 parameters and we have only 3 persons (classes) in the database.



A Mini-Batch Discriminative Feature Weighting Algorithm

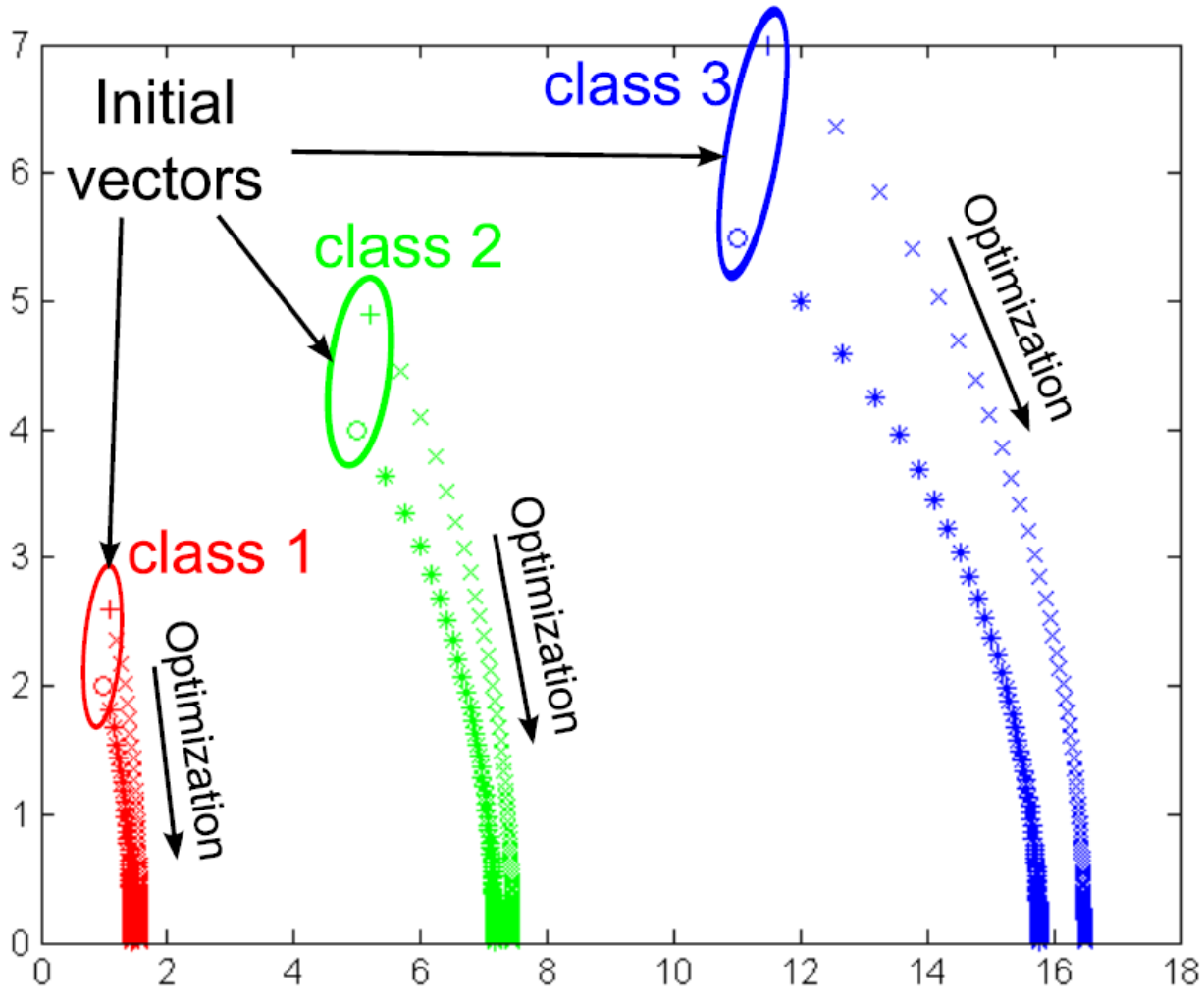
Before optimization:

- Precision 100%
- each class is described with 2 parameters

After optimization:

- Precision 100%
- each class is described with 1 parameter

Data compression with same precision



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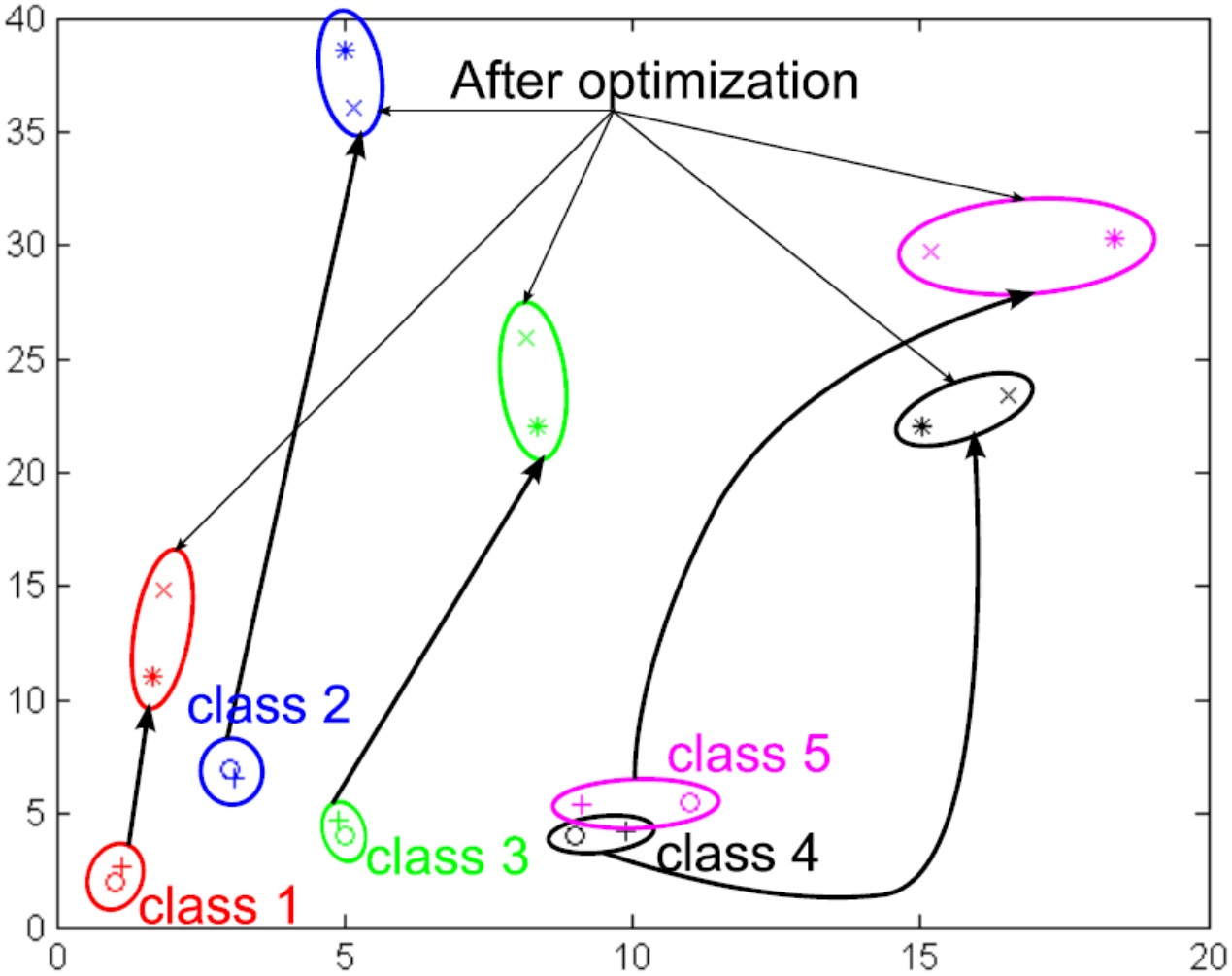
INSTITUTE OF ELECTRONICS AND COMPUTER SCIENCE

A Mini-Batch Discriminative Feature Weighting Algorithm

Each face is described with N=16384 LBT parameters.

Lets simplify the task:

Lets consider that each face (class) is described with 2 parameters and we have 5 persons (classes) in the database.



A Mini-Batch Discriminative Feature Weighting Algorithm

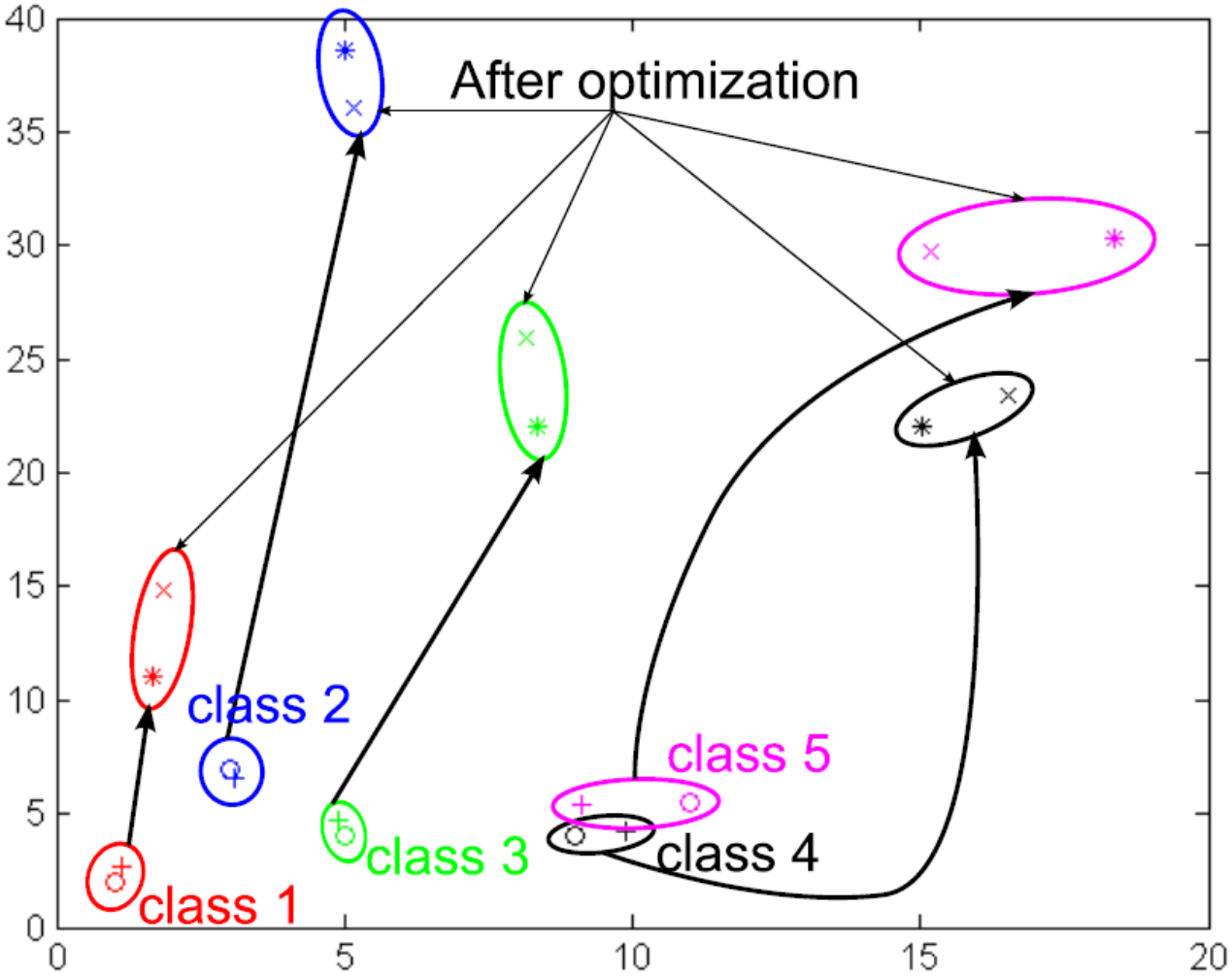
Before optimization:

- Precision **60%**
- each class is described with 2 parameters

After optimization:

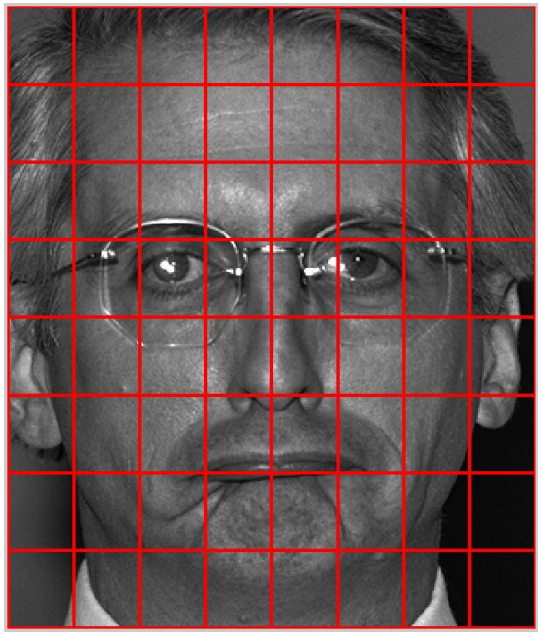
- Precision **100%**
- each class is described with 2 parameter

Recognition accuracy is improved

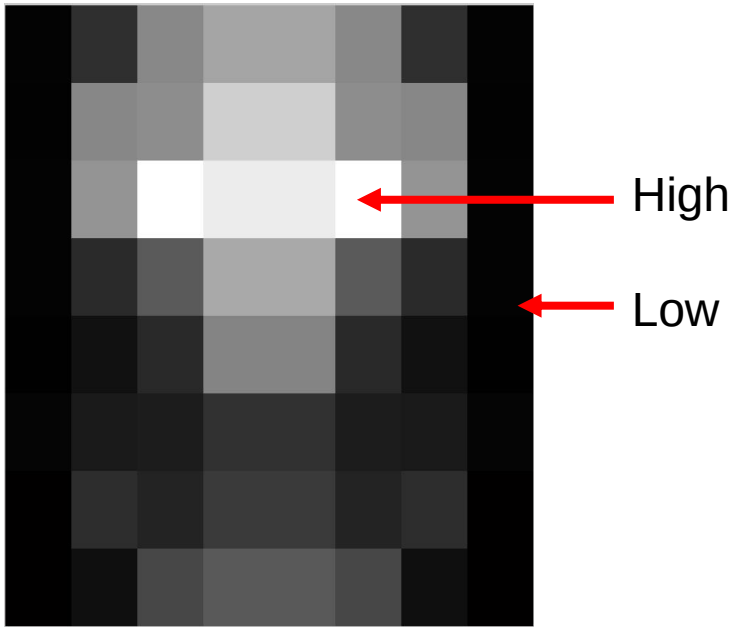


Results on FERET face database

Input face



Block weights



MIT and Harvard University research:

Title: 19 important results regarding face recognition by humans.

One of the facts was: *"of the different facial features, eyebrows are among the most important for recognition".*

Results on FERET face database

Number of persons in the database is almost 1000
2 frontal face images per person are available

fa and **fb** sets	MSLBP	MSLBP + feature weighting	MSLBP + block weighting
"Optimal" learning data	96,8 %	98.1 %	**99.2 %**

Thank You!