# FingerNet: An Unified Deep Network for Fingerprint Minutiae Extraction

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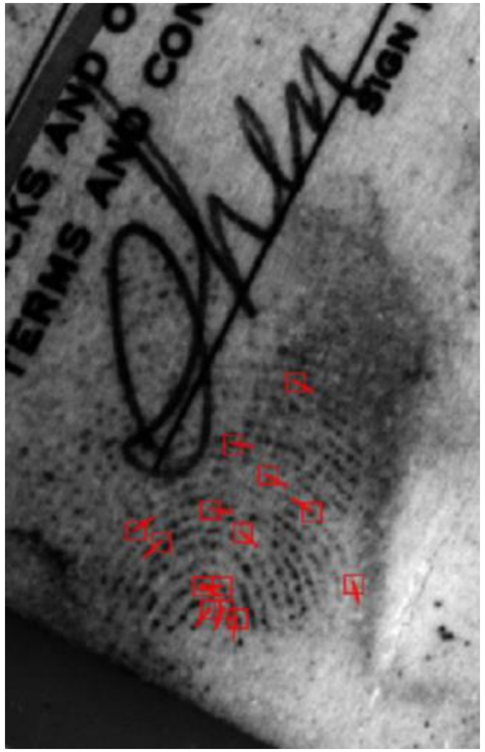
# Contents

# Backgrounds

1. Ten-print fingerprint：
   - Controlled condition (rolled/slap)
   - Automated minutiae extraction
2. Latent fingerprint：
   - Uncontrolled condition (crime scenes)
   - Manually marked by experts

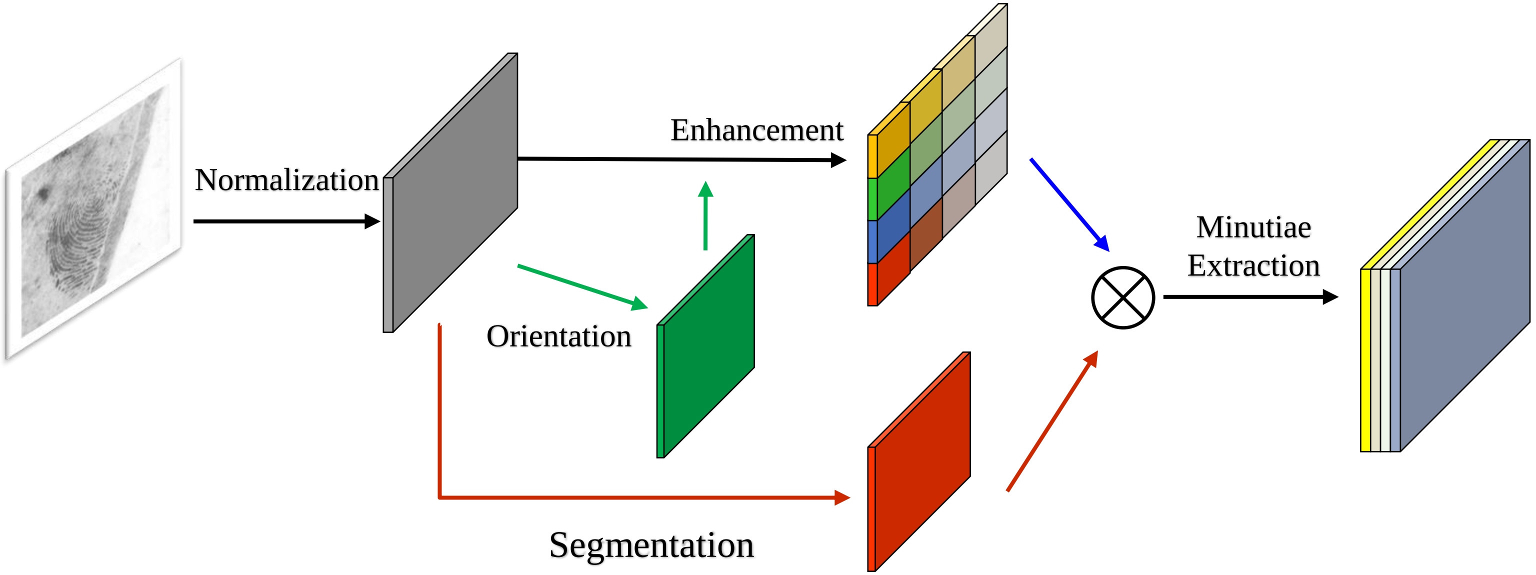


Left: Ten-print (FVC2002) , right: Latent (NIST SD27)

# Minutiae Extraction

1. Traditional method

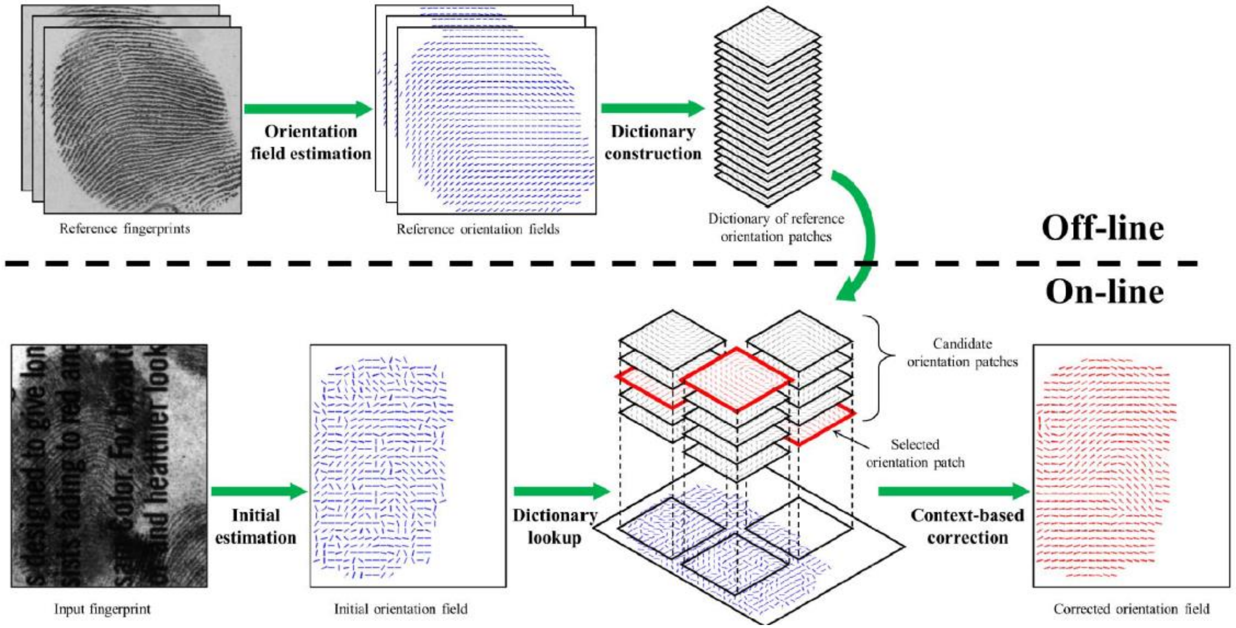
- Hand-crafted features designed by domain knowledge




Traditional minutiae extraction pipeline

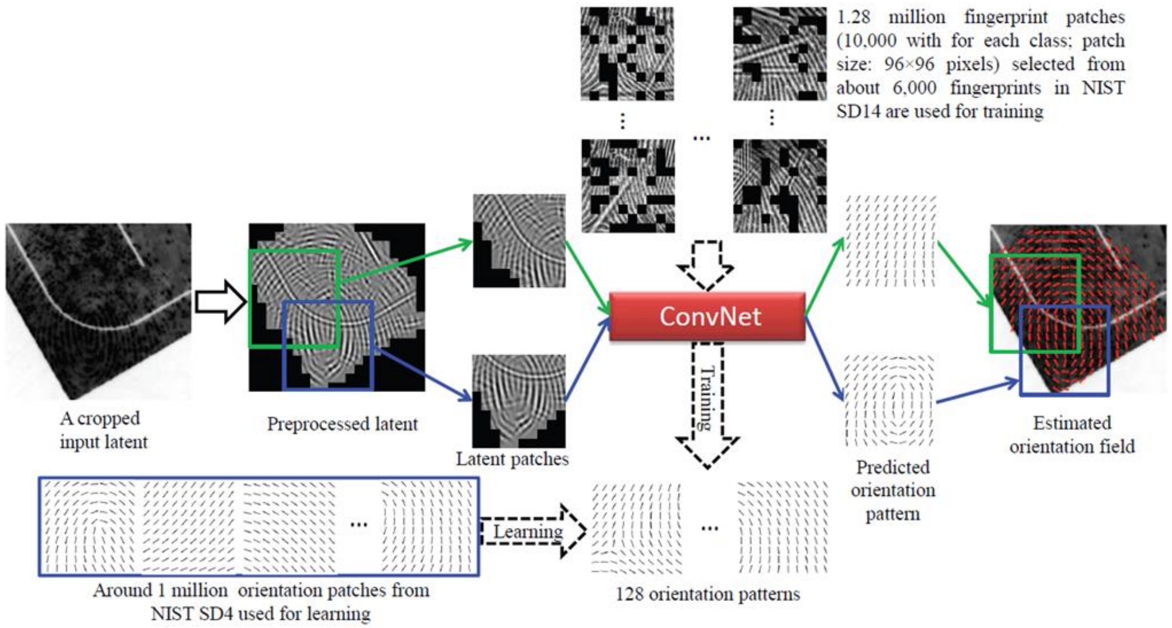
# Minutiae Extraction

Orientation estimation: Global dictionary (Feng J et al. 2013)



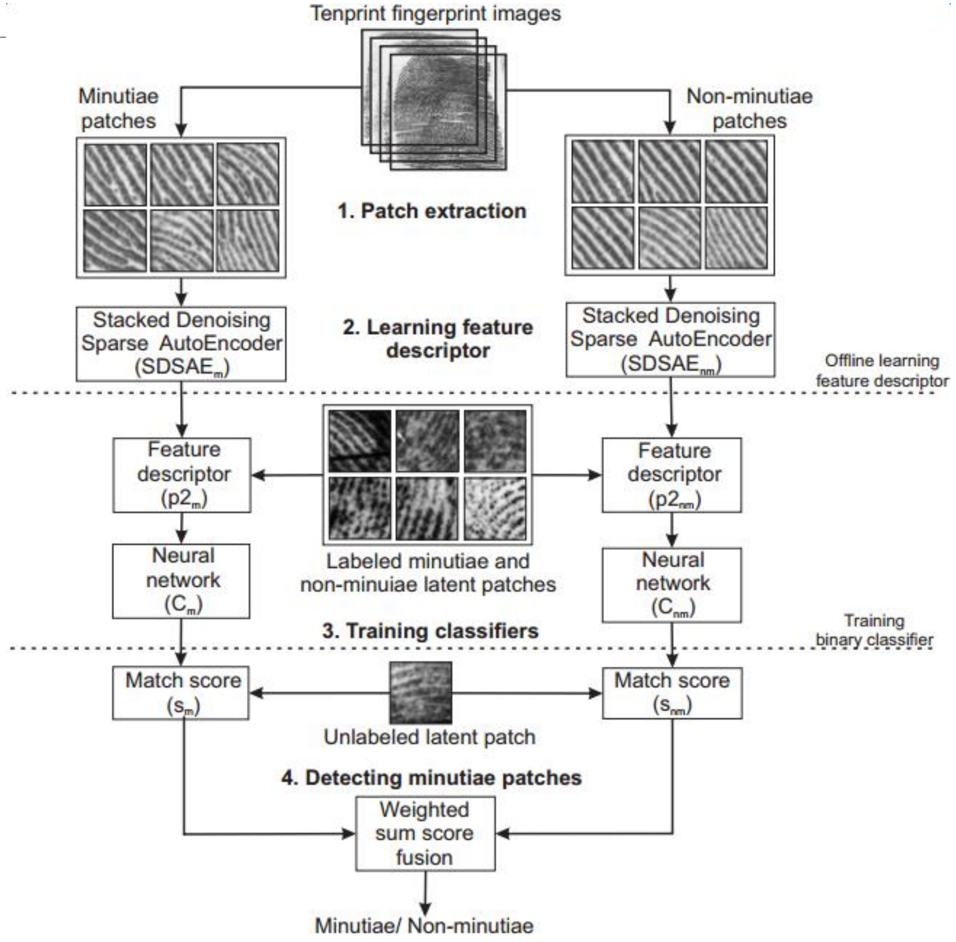
# Minutiae Extraction

Orientation estimation: ConvNet (Cao K et al. 2015)



# Minutiae Extraction

2. Leaning-based method
   - Toward latent fingerprints
   - Learning features from data
   - End-to-end

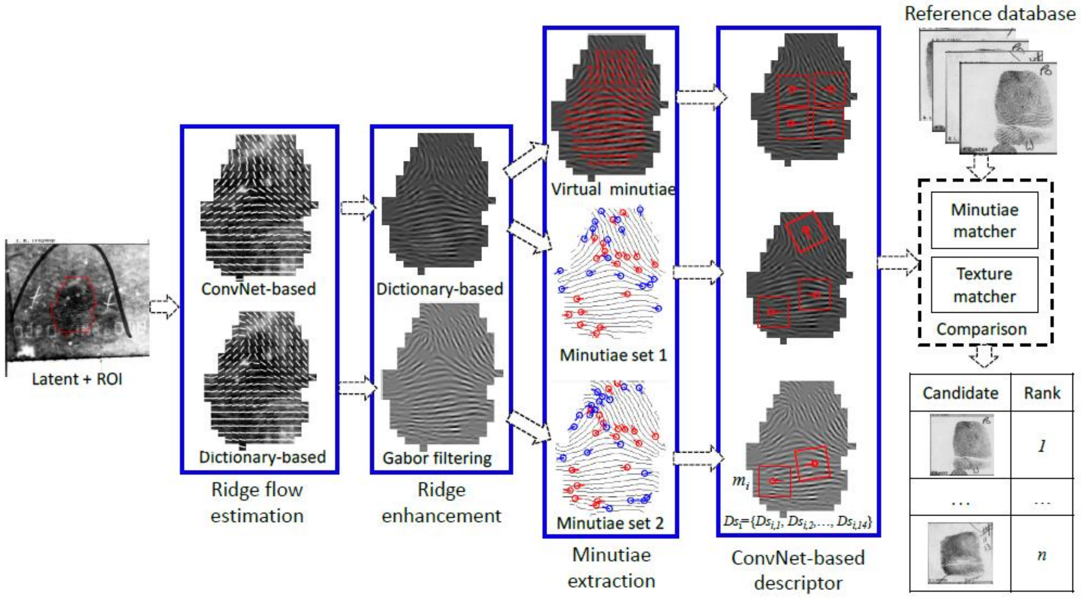



Stacked denoising autoencoders. Sankaran A et al. 2014

# Minutiae Extraction

## 2. Leaning-based method

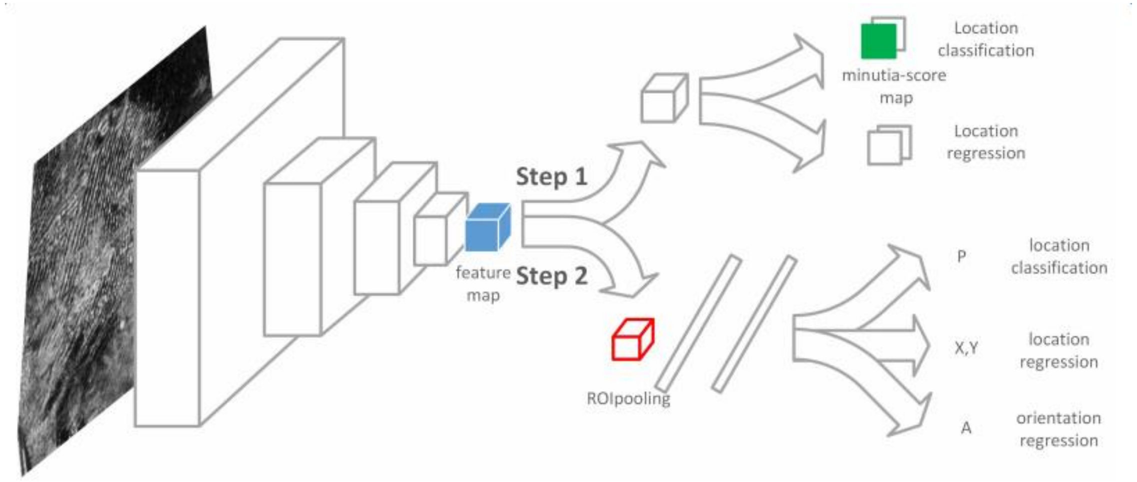
- Two minutiae templates




Automated Latent Fingerprint Recognition.
Cao K et al. 2017

# Minutiae Extraction

3. Previous work
- Detection task
- Deep learning
- End-to-end




Faster R-CNN based minutiae detection.
Tang Y et al. 2016

# Motivation

1. Combining domain knowledge and deep learning
   - Integrating fingerprint characteristics to make the model interpretable and transferable
   - Learning from data to make the model more robust to noise

# One question

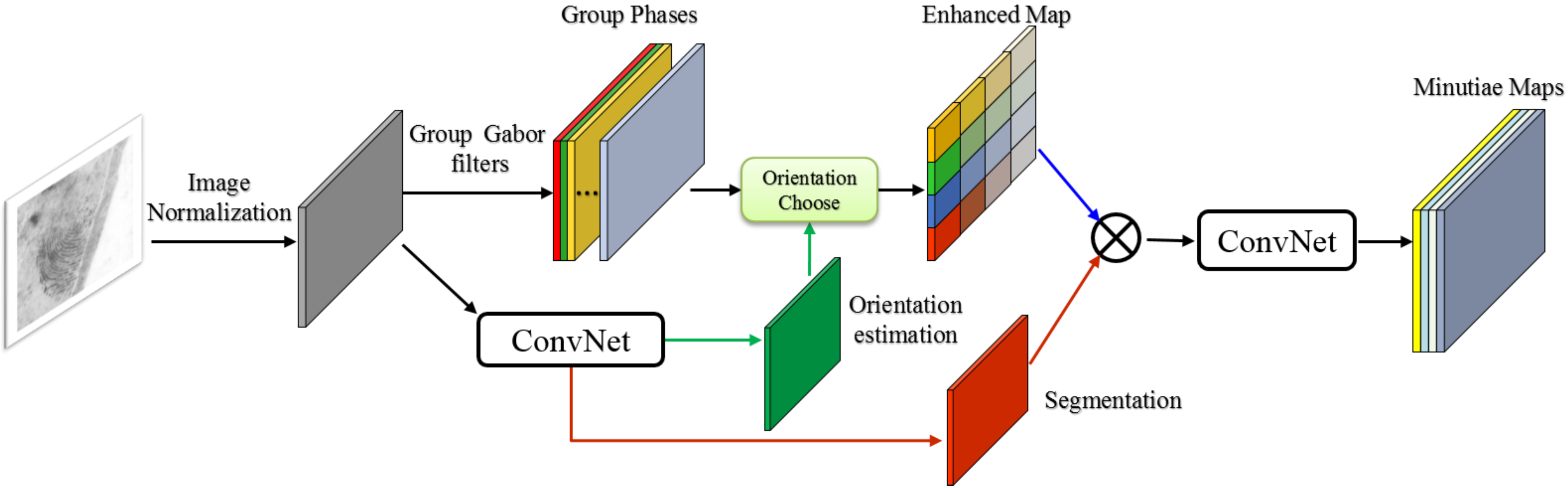
What’s the relationship between traditional method and deep learning?

- Traditional method is equivalent to a simple shallow ConvNet with fixed weights

# Traditional methods to equivalent ConvNet

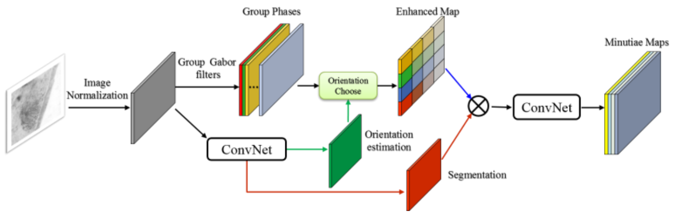
Convolutional operation—>convolutional layer

Pixel-wise operation—>activation layer/combined layer




Plain FingerNet: Integrated minutiae extraction pipeline

# Plain FingerNet




## Transform traditional methods

1. Orientation estimation (Nalini K Ratha et al. 1995)

$$G_{xy} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_x(x_i + h, y_i + k) \cdot \nabla_y(x_i + h, y_i + k),$$

$$G_{xx} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_x(x_i + h, y_i + k)^2,$$

$$G_{yy} = \sum_{h=-8}^{8} \sum_{k=-8}^{8} \nabla_y(x_i + h, y_i + k)^2,$$

$$\theta = 90^\circ + \frac{1}{2} atan2(2 \cdot G_{xy}, G_{xx} - G_{yy}),$$

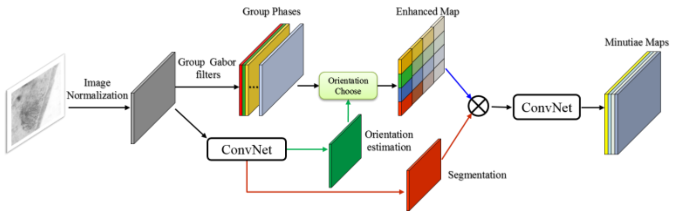
$$\nabla_x I = I * S_x, \ \nabla_y I = I * S_y,$$

$$G_{xy} = (\nabla_x I \cdot \nabla_y I) * J_w,$$

$$G_{xx} = (\nabla_x I)^2 * J_w,$$

$$G_{yy} = (\nabla_y I)^2 * J_w,$$

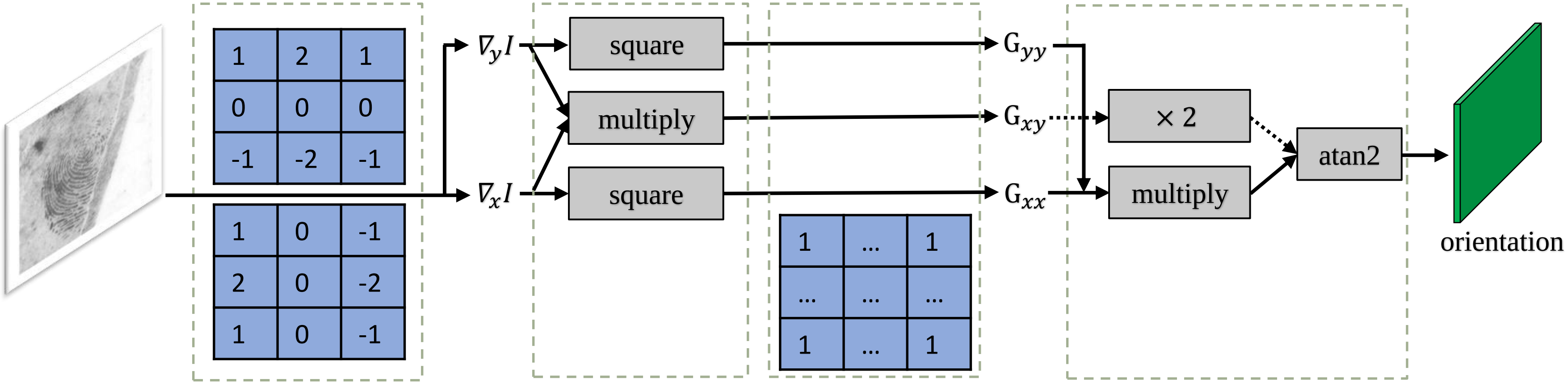
$$\theta = 90^\circ + \frac{1}{2} atan2(2 \cdot G_{xy}, G_{xx} - G_{yy}),$$



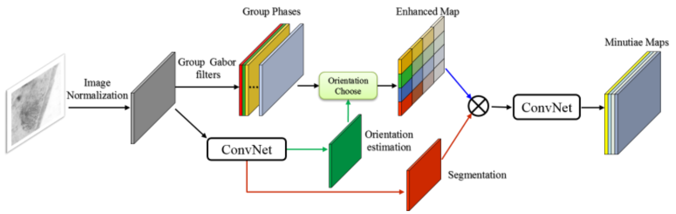

# Plain FingerNet

## Transform traditional methods

1. Orientation estimation (Nalini K Ratha et al. 1995)
   - 3 hand-crafted features, complex connection and activation function




Orientation estimation module




# Plain FingerNet

## Transform traditional methods

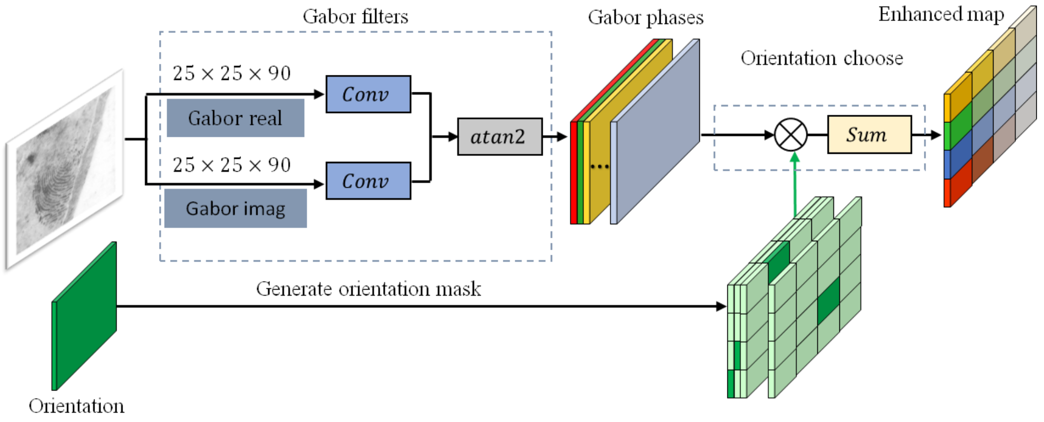
### 2. Enhancement (Gao X et al. 2010)

- Grouped phases: generate enhanced phases C on every orientation
- Orientation choose: generate a mask M according to orientation
- M*C

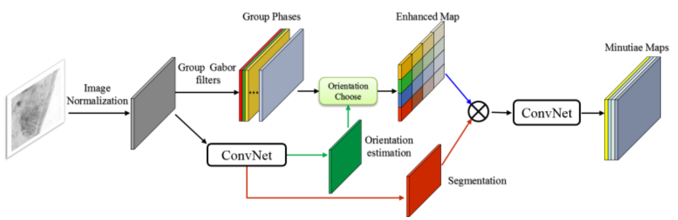
$$C(x,y,i) = (I * g_{\omega_i,\theta_i})(x,y),\ i = 0,1,\dots,N-1$$
$$F(x,y,i) = Arg[C(x,y,i)].$$

$$M(x,y,i) = \begin{cases} 1, & if\ \omega(x,y) = \omega_i,\ \theta(x,y) = \theta_i \\ 0, & otherwise. \end{cases}$$

$$E(x,y) = \sum_{i=0}^{N} F(x,y,i) \cdot M(x,y,i)$$




Enhancement module




# Plain FingerNet

## Transform traditional methods

### 3. Extraction

- Template matching
- Conv + maxout activation

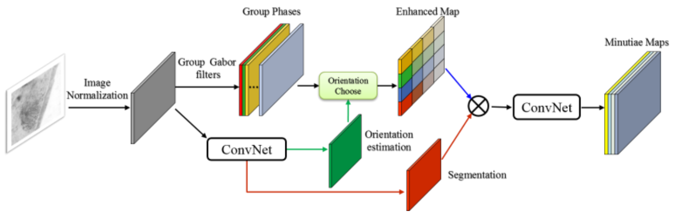
$$S(x, y) = \max_t (E * T_t)(x, y),$$

Extraction templates. Black, white and gray represent 0, 1 and arbitrary pixels respectively

# Expand to FingerNet

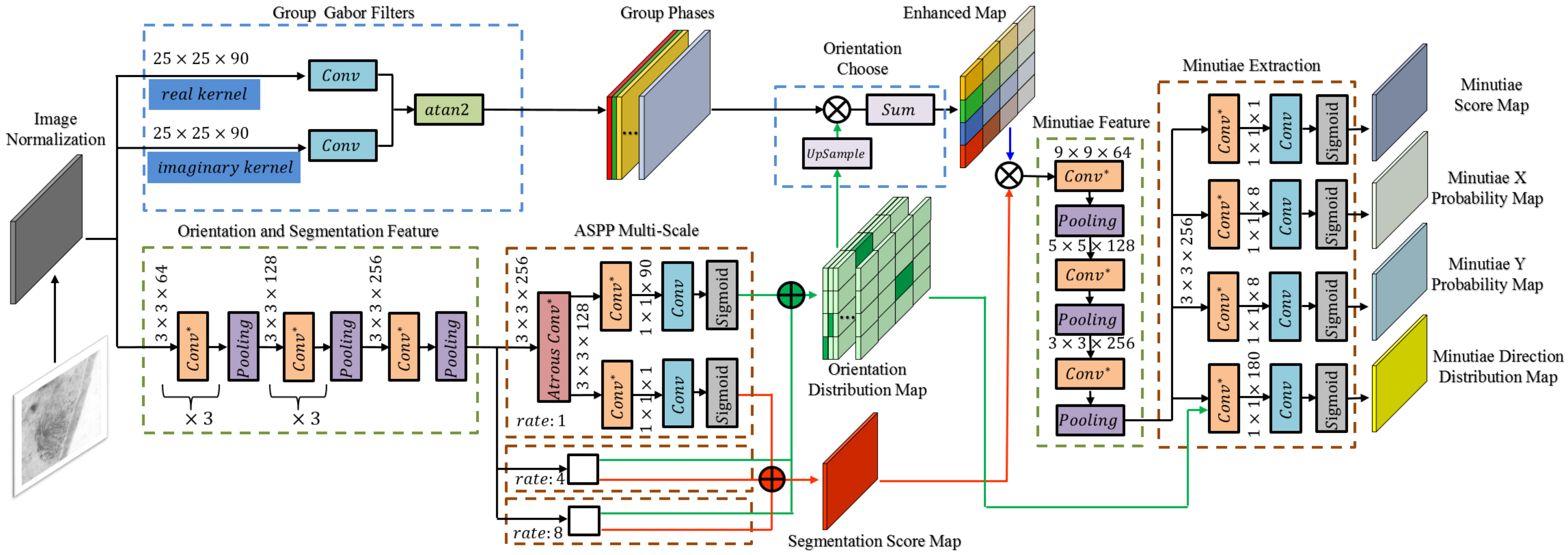
1. Plain FingerNet:
    - Fixed weights
    - Shallow layers
2. Complete FingerNet:
    - Release weights: learn complex background variance from data
    - Expand layers: enhance representation ability

# Expand to FingerNet

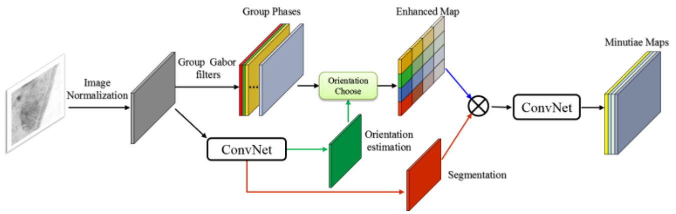



## Detailed FingerNet architecture

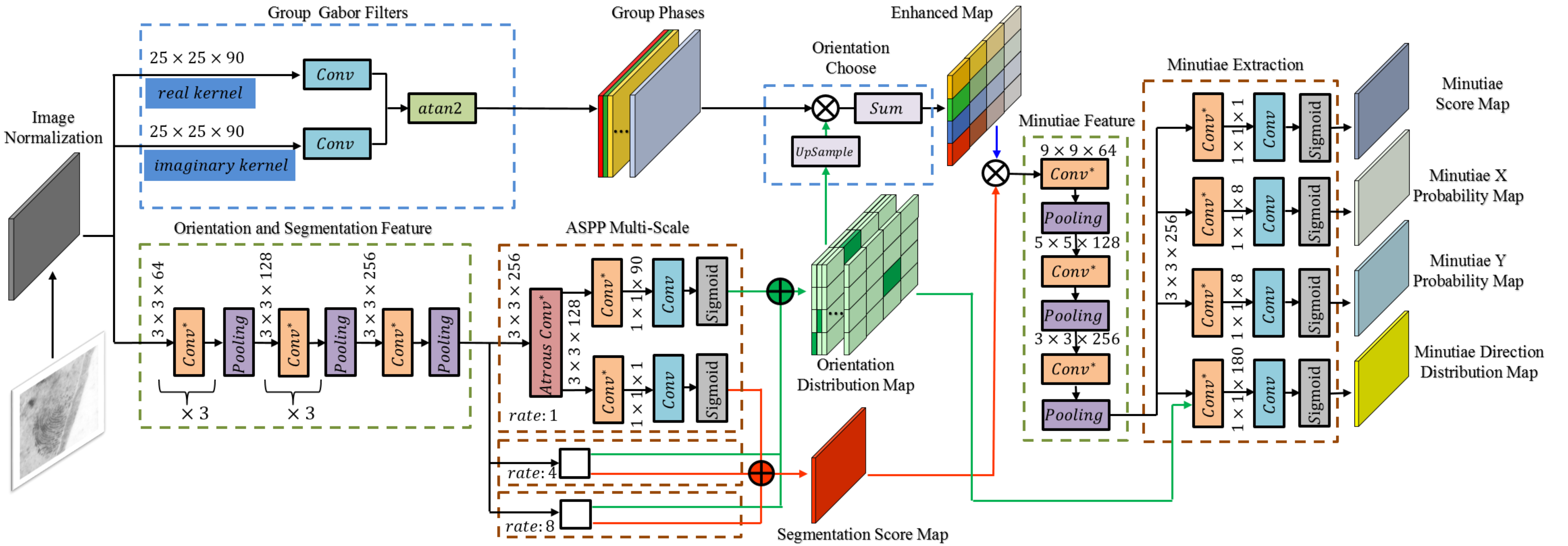
- Expanded from the plain FingerNet
- Trained end-to-end

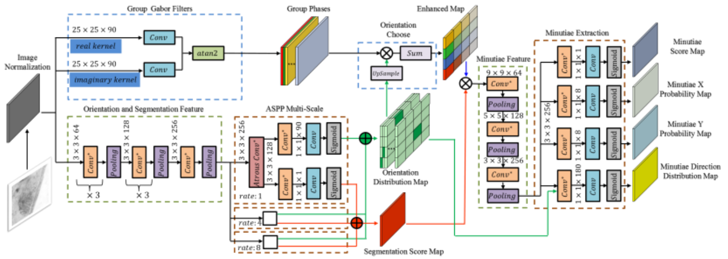


# How to train?




Label, Loss and training.





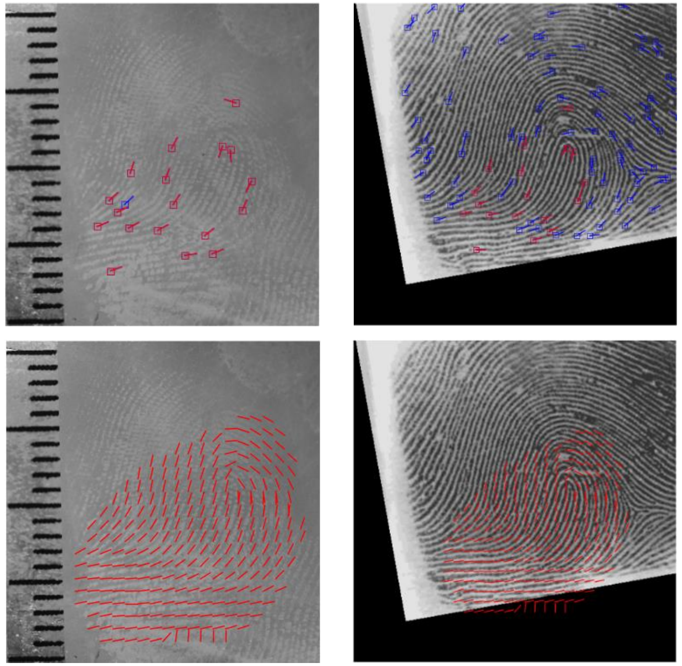
# Label

Weak, strong and ground truth label:

- Weak orientation： from corresponding ten-print fingerprint (minutiae alignment)
- Strong orientation： minutia direction
- Weak segmentation： minutiae convex hull
- Ground truth minutia： manually marked

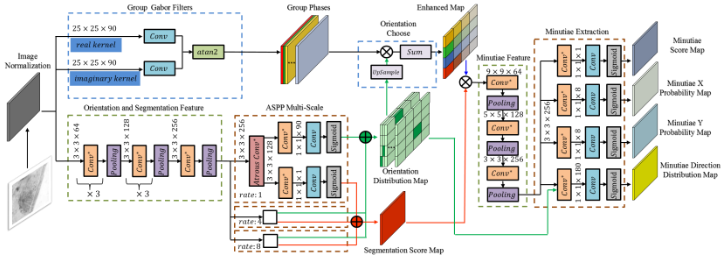
Figure on the right:

- Weak label generation

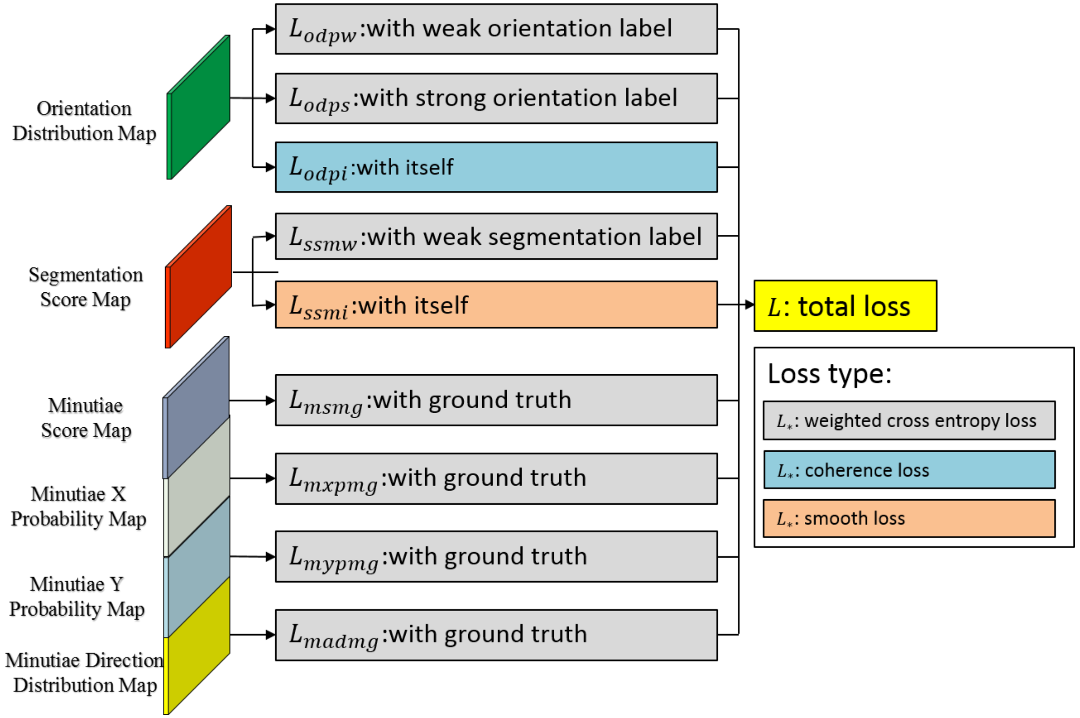


Top: minutiae alignment
Down: orientation replication

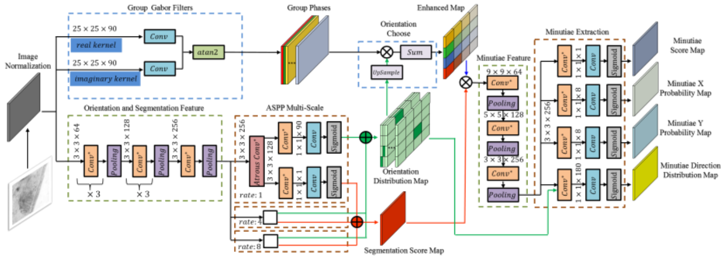
# Loss



Loss cluster: a weighted sum of 9 different losses from orientation, segmentation and minutiae extraction



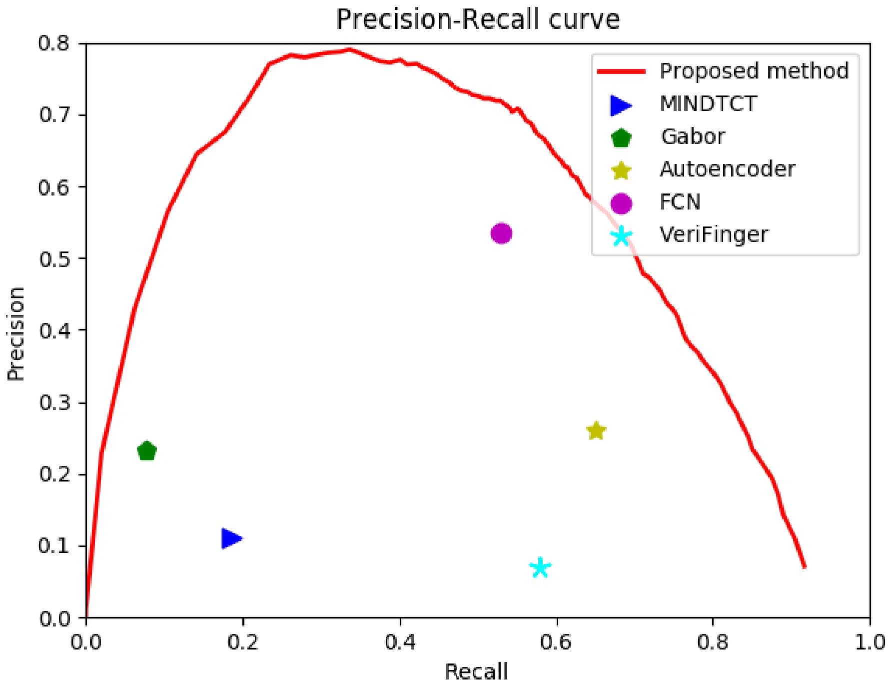
# Training



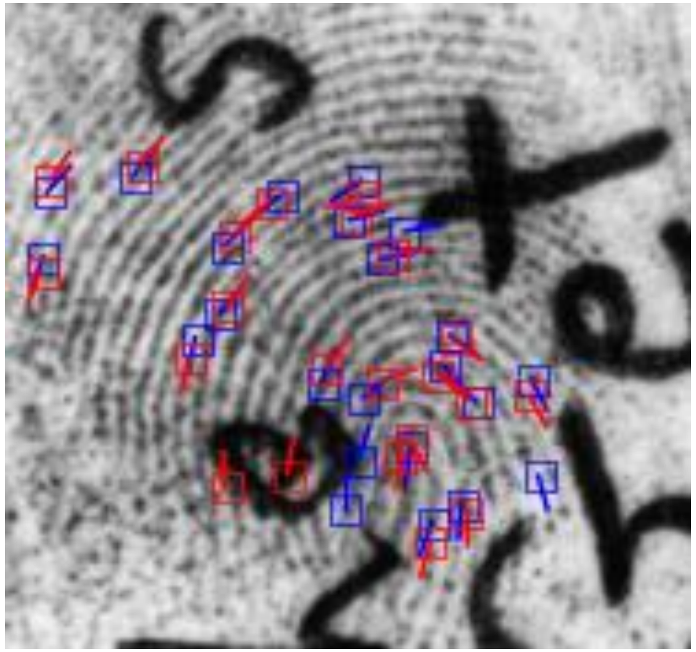

1. Two steps training:
   a) Training orientation and segmentation modules for a few epoches
   b) Training the whole FingerNet by all the losses
2. Training data:
   - 8000 pairs of matched rolled fingerprints and latent fingerprints. Latent fingerprints include manually marked minutiae. Rolled fingerprints are used to generate weak labels.

# Experiments

## Minutiae extraction on NIST SD27




Precision-Recall curves on NIST SD27



A sample for extracted minutiae. Red denotes our results and blue denotes manually marked minutiae.

# One more thing!

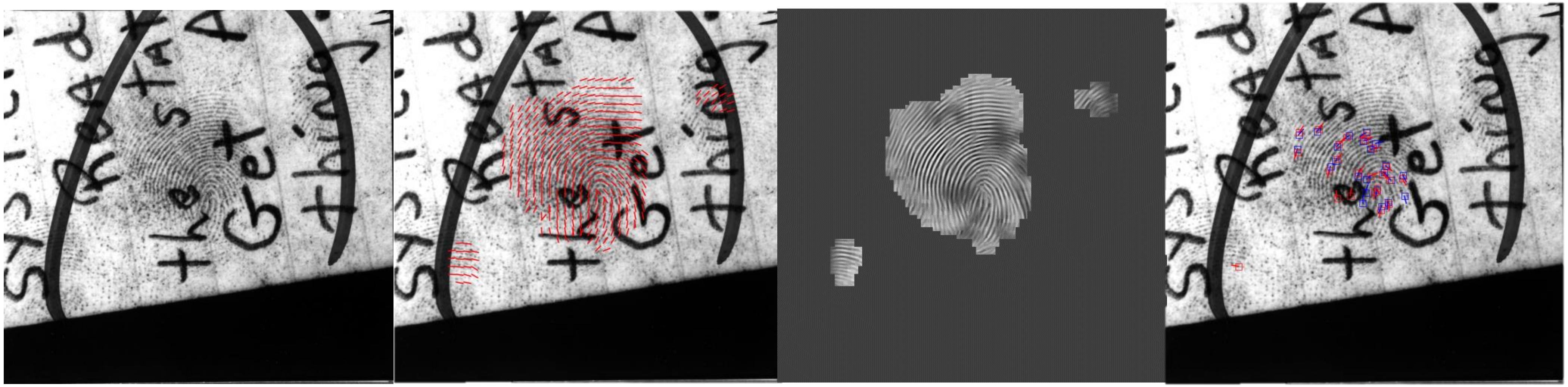
Benefit from the combination of deep learning and domain knowledge:

1. Interpretable: typical fingerprint representations including orientation field, segmentation and enhancement can be acquired from intermediate layer.

2. Transferable: it also performed well on other datasets without any fine-tuning.

# Experiments

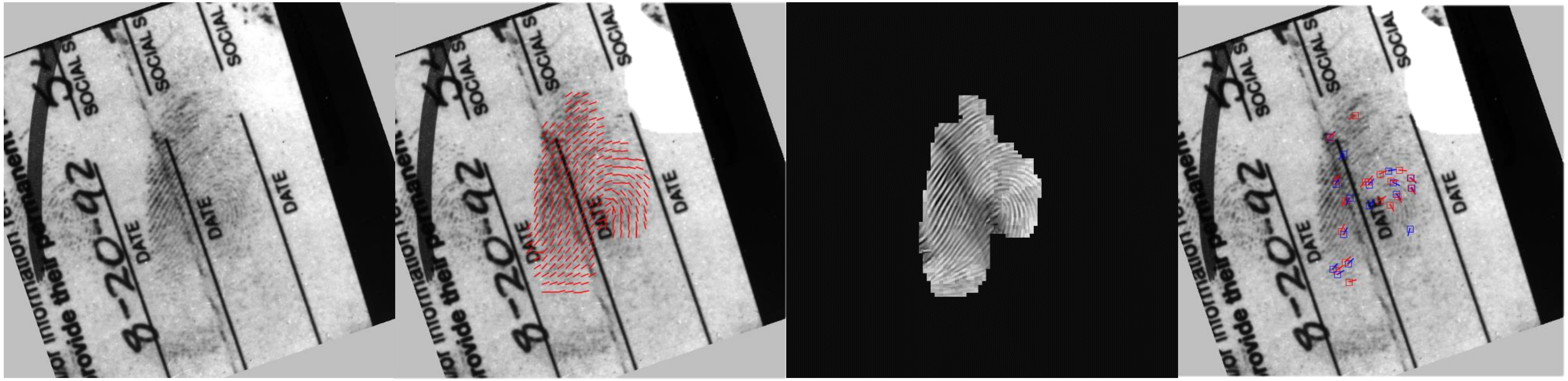
## More results on NIST SD27 (Good)



From left to right: original fingerprint, segmented orientation field, enhance fingerprint and minutiae map.

# Experiments

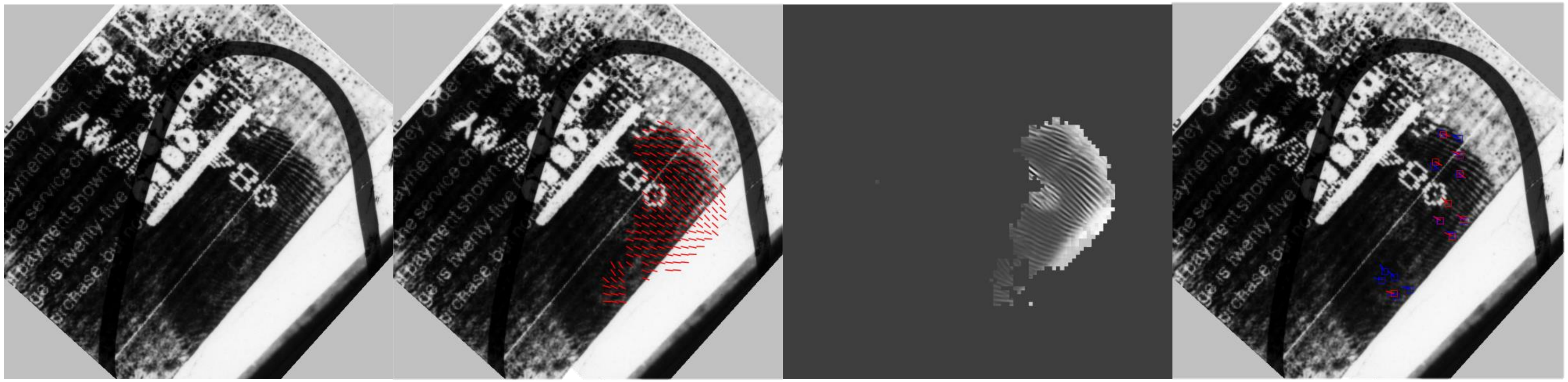
## More results on NIST SD27 (Bad)



From left to right: original fingerprint, segmented orientation field, enhance fingerprint and minutiae map.

# Experiments

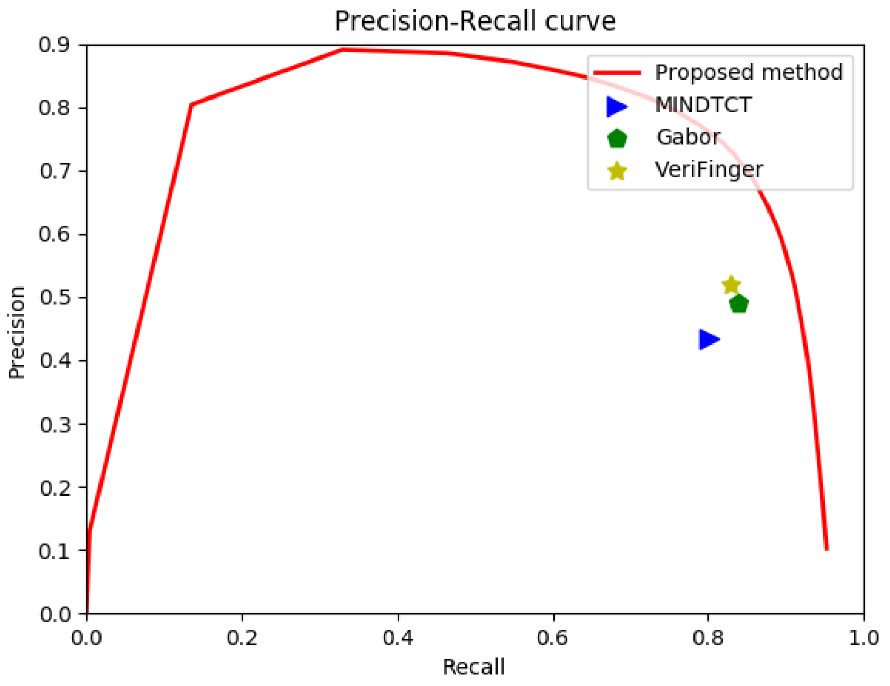
## More results on NIST SD27 (Ugly)



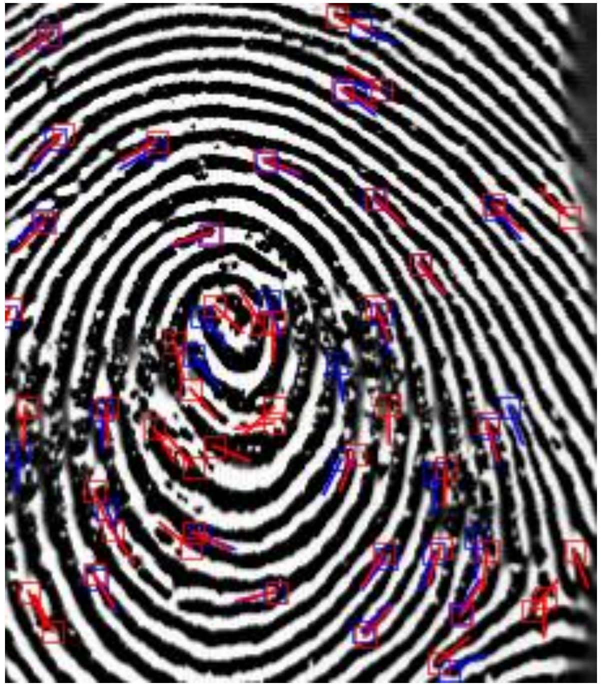
From left to right: original fingerprint, segmented orientation field, enhance fingerprint and minutiae map.

# Experiments

## Minutiae extraction on FVC2004



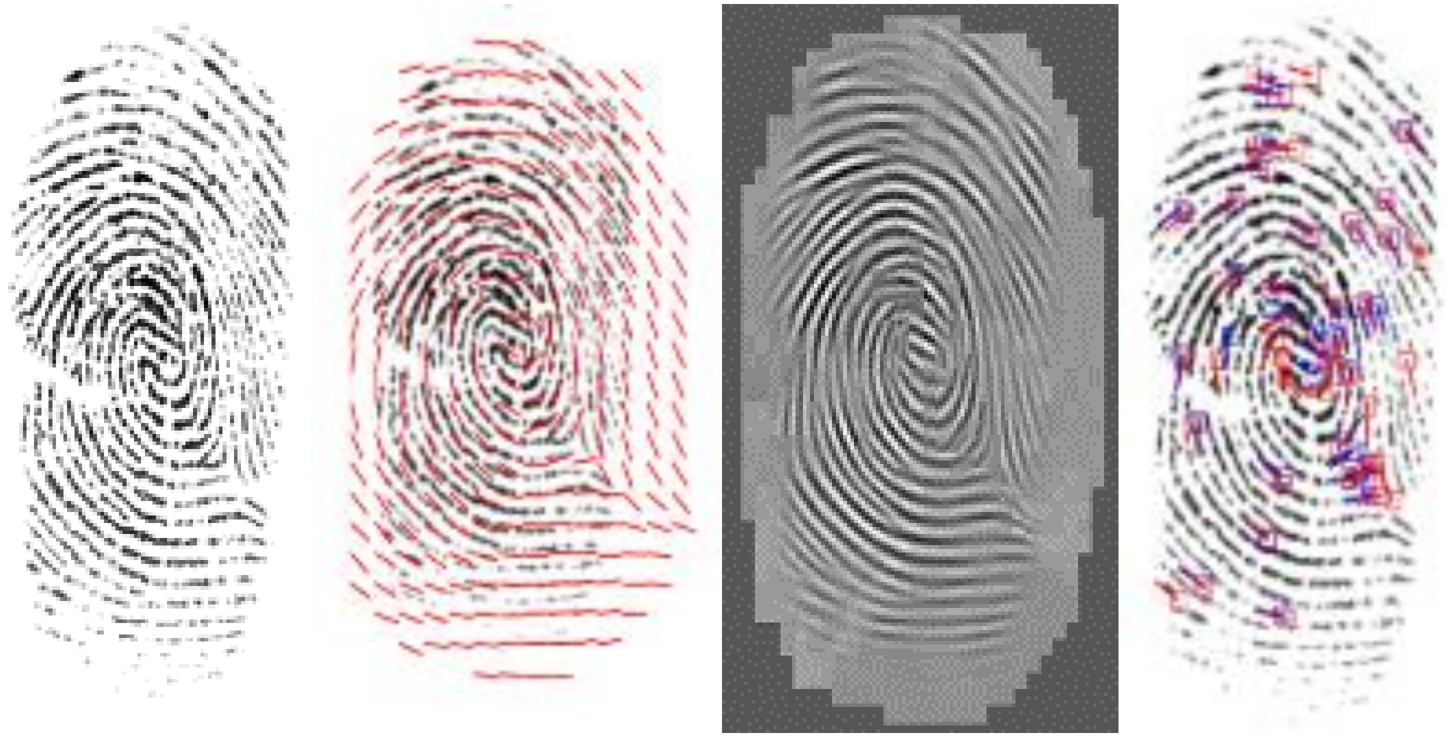

Precision-Recall curves on NIST SD27



A sample for extracted minutiae. Red denotes our results and blue denotes manually marked minutiae.

# Experiments

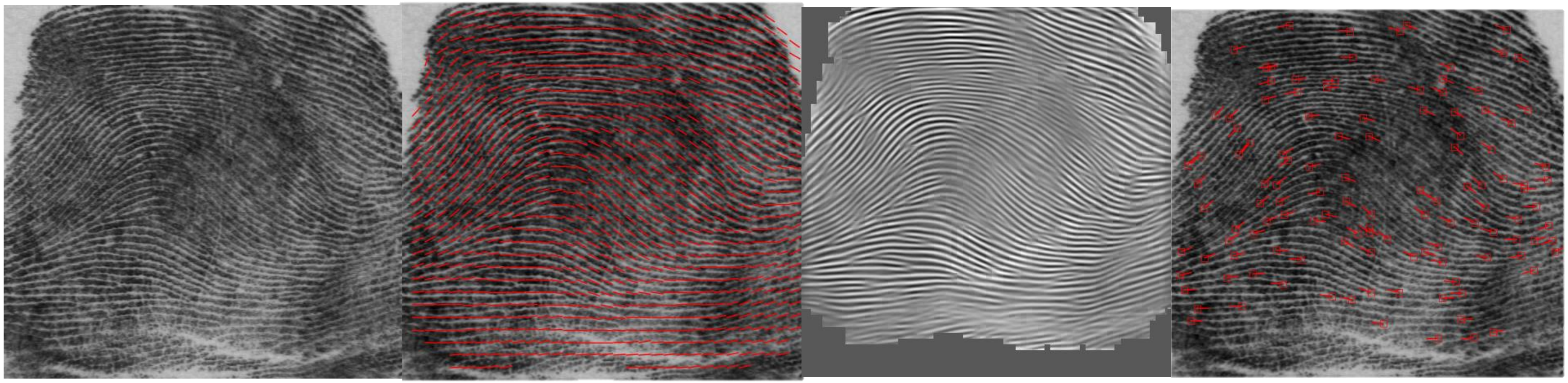
## More results on FVC2004



From left to right: original fingerprint, segmented orientation field, enhance fingerprint and minutiae map.

# Experiments

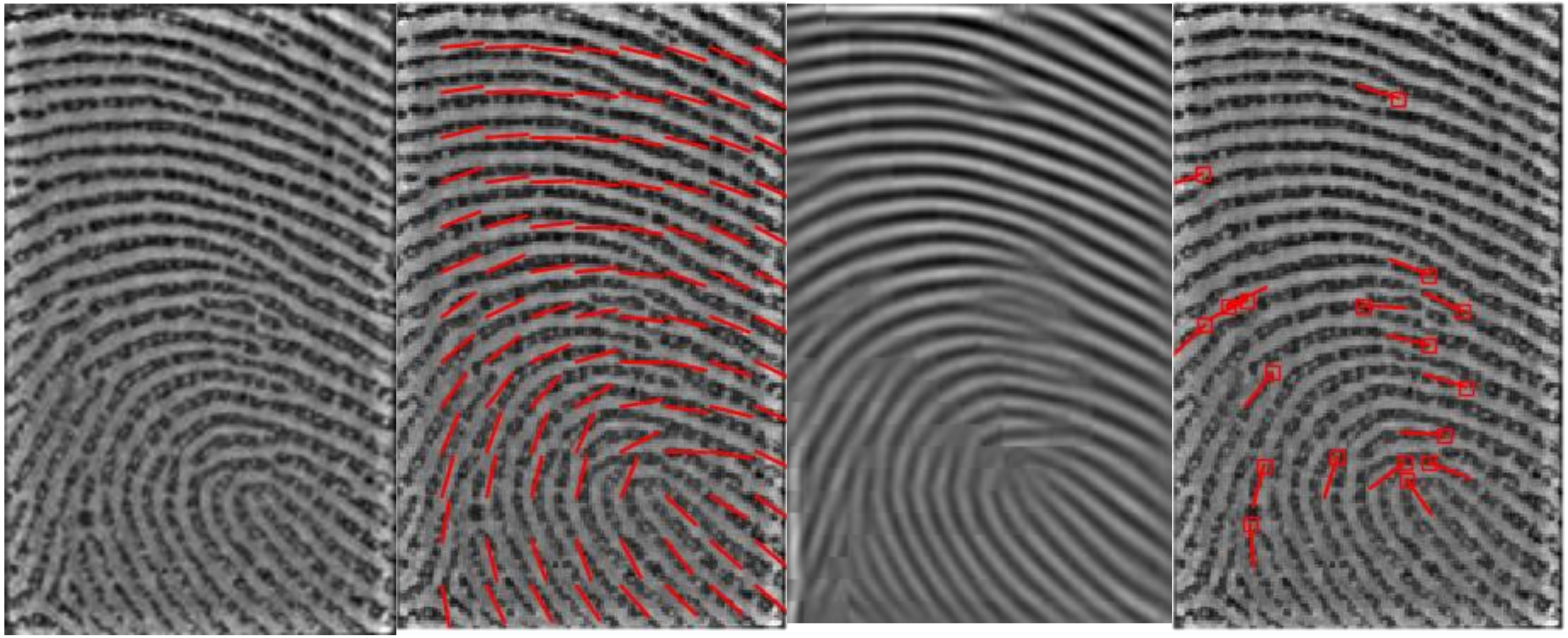
## More results on NIST 4



From left to right: original fingerprint, segmented orientation field, enhance fingerprint and minutiae map.

# Experiments

## More results on high-resolution partial fingerprint



From left to right: original fingerprint, segmented orientation field, enhance fingerprint and minutiae map.

# Conclusions

1. A new way to guide the deep network's structure design for combining domain knowledge and deep learning representation ability.
2. FingerNet is proposed to extract reliable minutiae on both ten-print and latent fingerprints. The network is interpretable and transferable.
3. One way to generate weak labels to help training.

# Thanks for your listening!

If you have any question, please email to:

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