
# 基于行为特征的人体识别技术

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# 目录

# --> 背景及研究意义

- 信息安全系统的需求逐渐增加
- 生物识别技术为计算机安全提供了友好和可靠的解决方案
- 机器学习技术的发展为生物识别技术提供了理论基础
- 行为生物特征研究相对较少

| 类别 | 举例 |
| --- | --- |
| 基于身份的特征 | 签字、手绘等 |
| 基于人机交互的特征 | 肌肉动作：使用键盘、鼠标的动作等 |
| | 高级行为：游戏技巧、使用软件的技能 |
| 基于非直接的人机交互的特征 | 下意识产生的行为，如：执行程序的方式等 |
| 动作技能 | 步伐、手势等 |
| 没有肌肉动作的行为特征 | 思考时的策略、技巧等 |

## 为什么要研究行为生物特征？

Behavioral vs Physical

- 方便采集数据
- 成本低
- 种类更多
- 研究相对较少
- 可以作为辅助特征提高识别率

# --> 研究现状

- 对于物理生物特征的研究已经相当成熟，并已广泛应用于实际生活当中
- 对于行为生物特征的研究相对较少，技术不够成熟
- 受外界影响因素比较多，如步态识别中的角度影响
- 由 Z. Wu 等人提出的方案中，在 CASIA-B 数据集上，对于正常、穿大衣、带包三种情况下的跨角度识别平均准确率分别为 94.0%、50.9%、73.3%

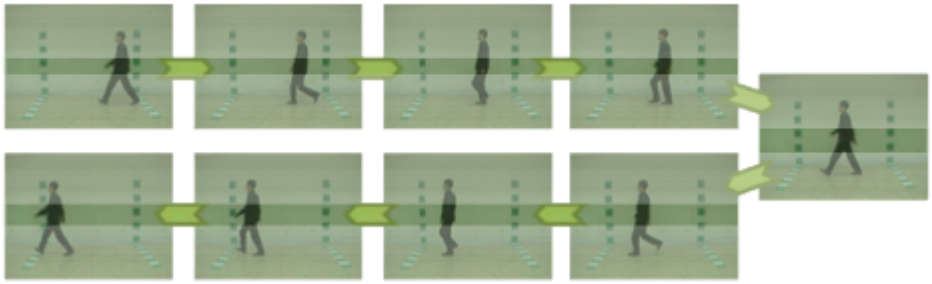
# --> 主要研究内容

## 步态识别（gait recognition）

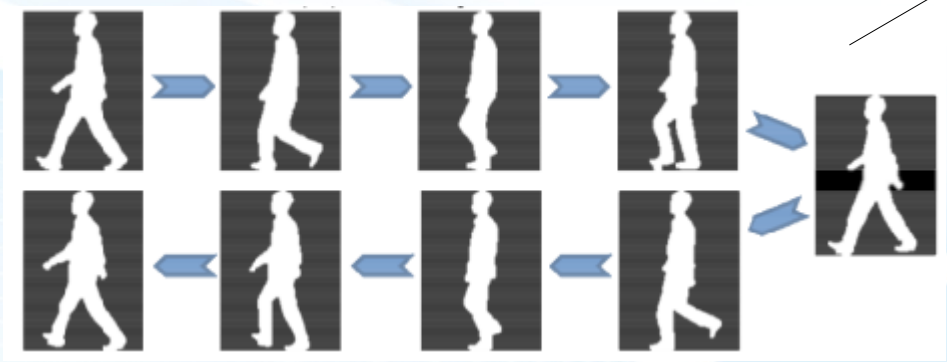
- 独特性高
- 持久性相对较好
- 数据易采集
- 可行性高
- 适合远距离识别

- 主要解决步态识别中由于角度变化而引起的识别率下降的问题

## GEI (Gait Energy Image)



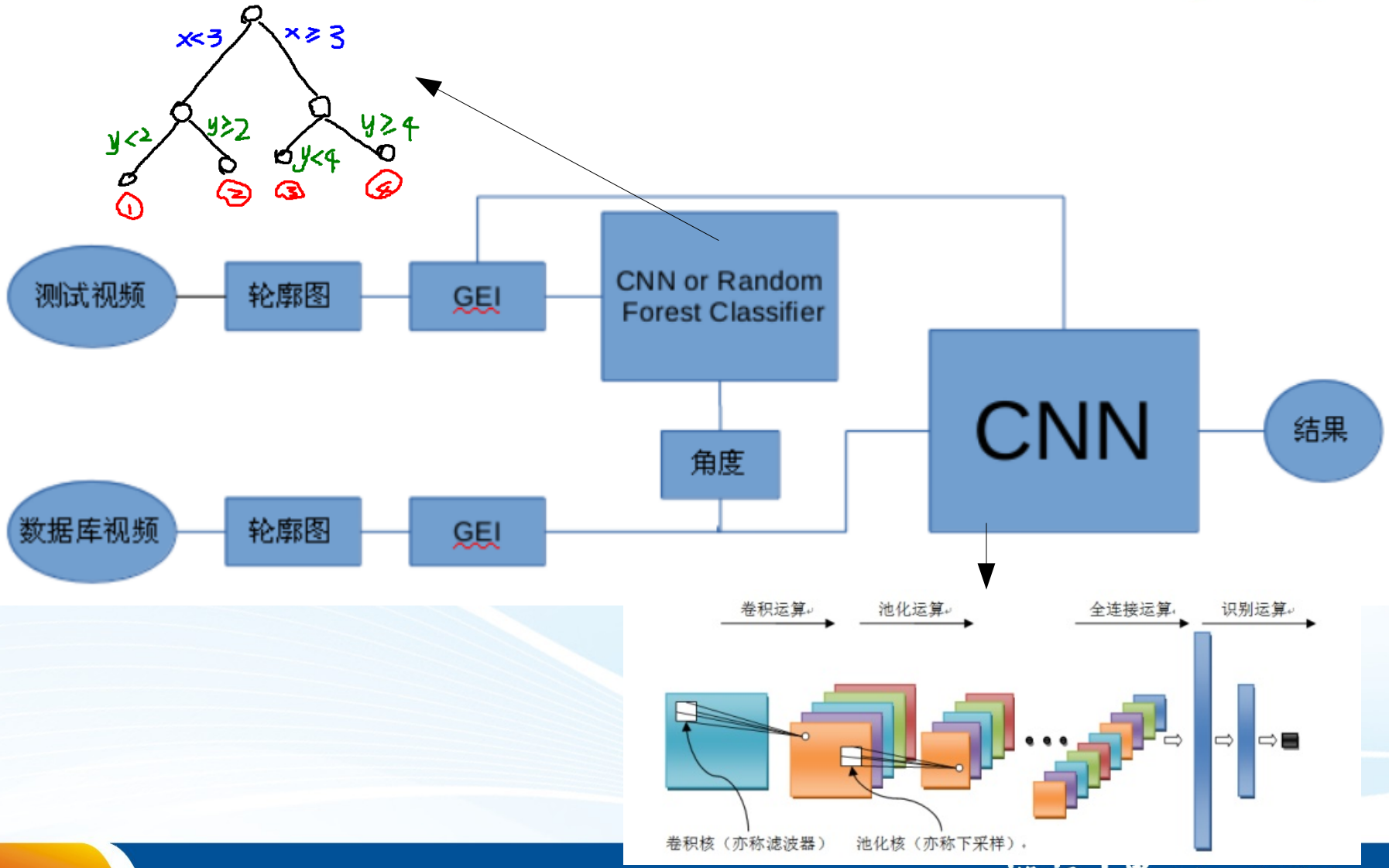
Key frames



Silhouette samples

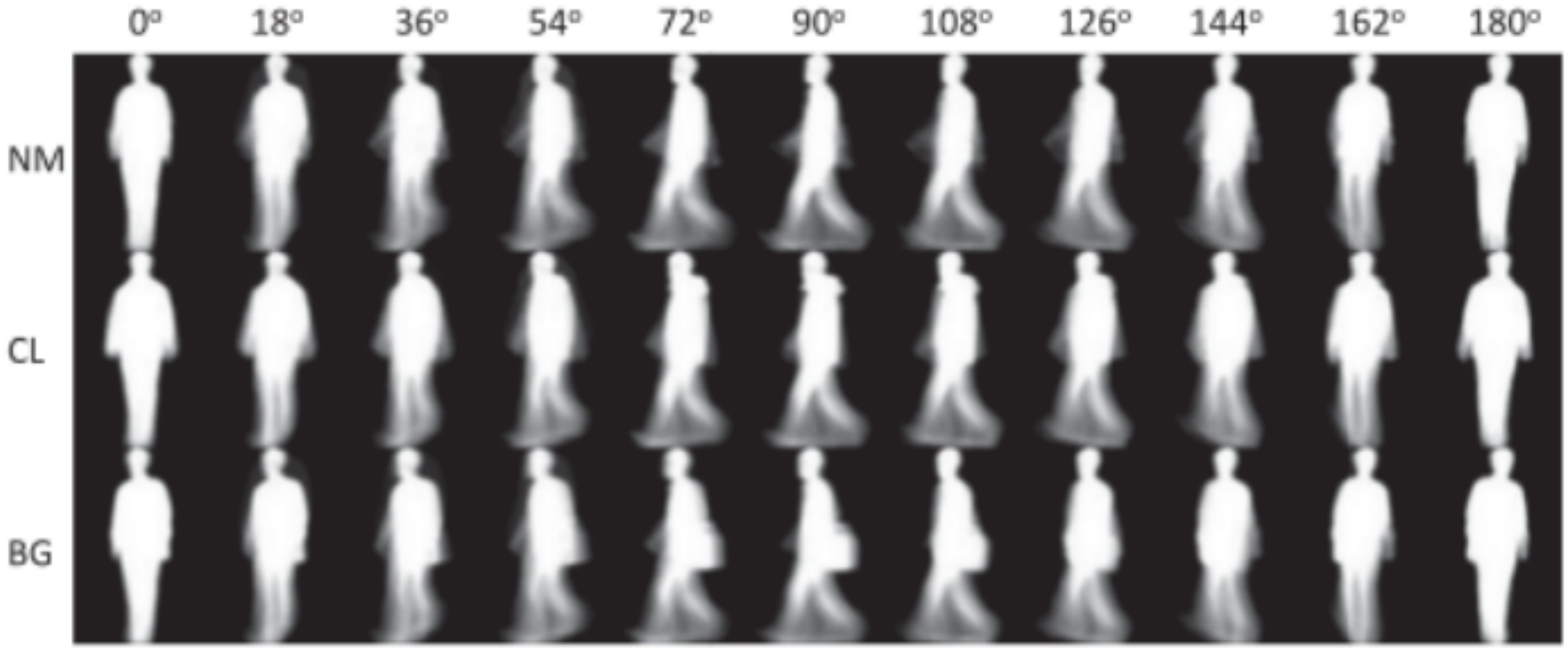
GEI

# --> 项目实施方案


x<3
x≥3
y<2
y≥2
y<4
y≥4
①
②
③
④
测试视频
轮廓图
GEI
CNN or Random Forest Classifier
角度
CNN
结果
数据库视频
轮廓图
GEI
卷积运算
池化运算
全连接运算
识别运算
卷积核（亦称滤波器）
池化核（亦称下采样）

# --> 实验

数据集：CASIA-B



# --> 实验

实现细节:

主要参数:

learning_rate=0.0001

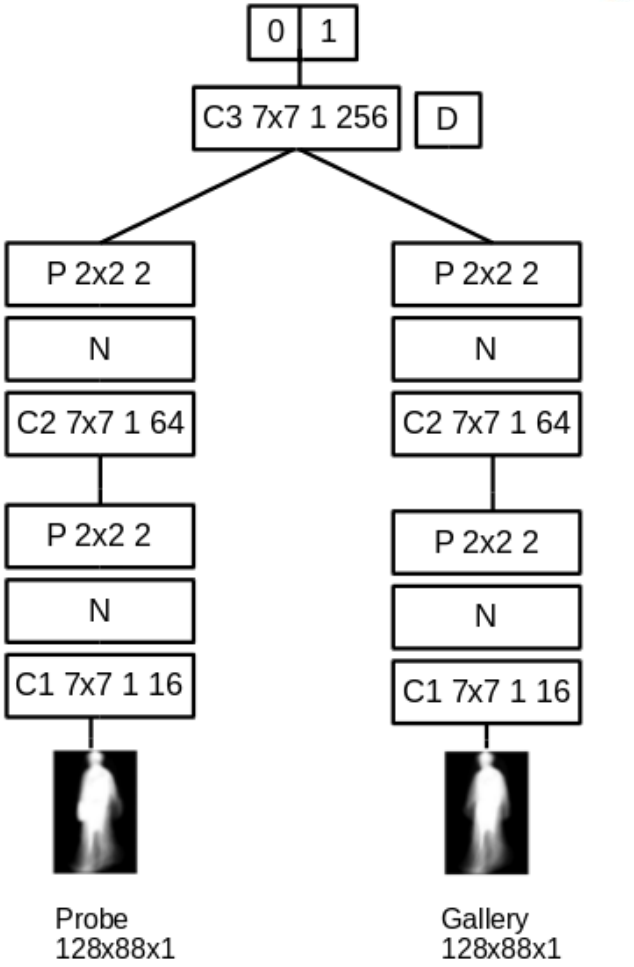
AdamOptimizer

train_steps=25000

batch_size=128

train_data={2500+,2500-}

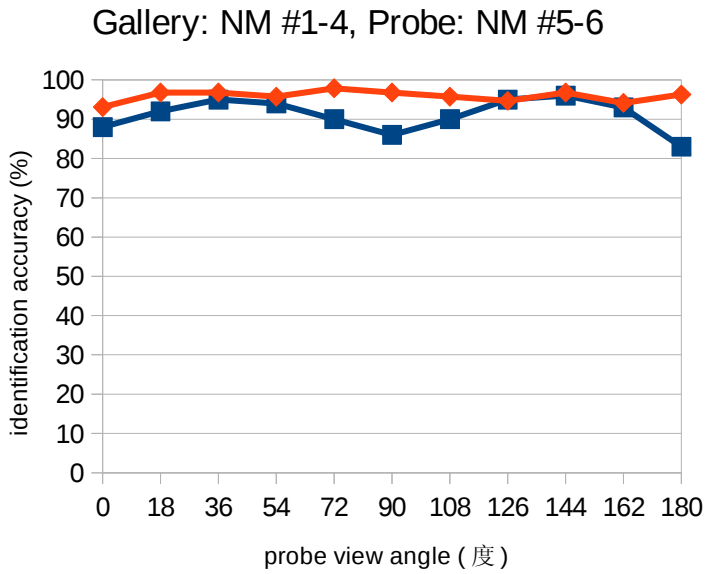
val_data={1000+,1000-}

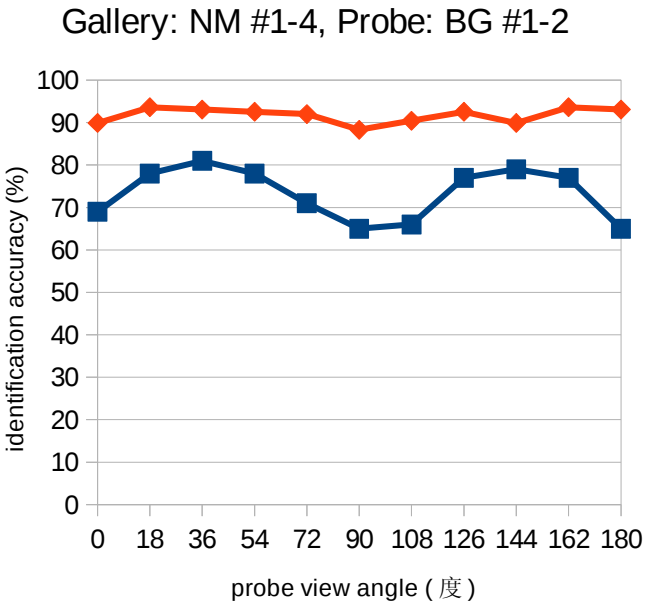


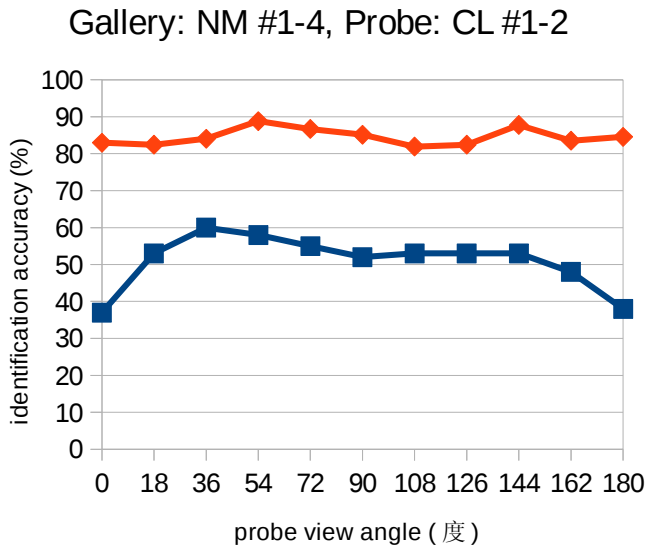

MT 网络

# --> 实验

结果:

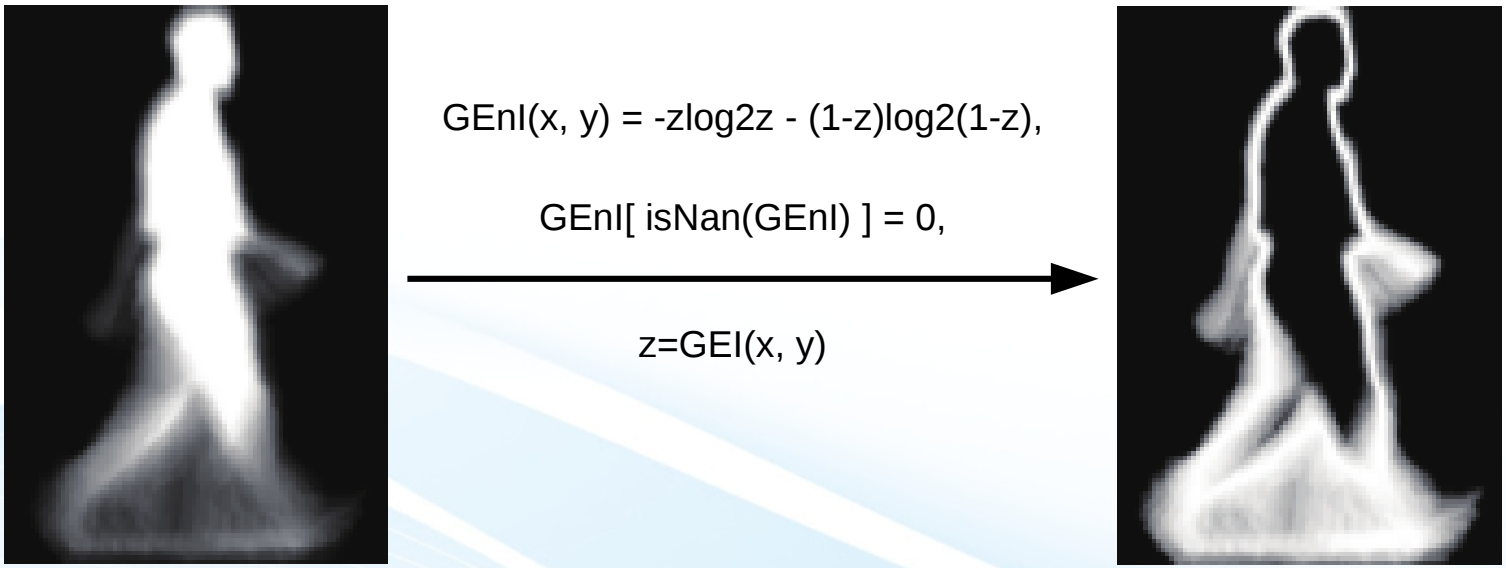

Gallery: NM #1-4, Probe: NM #5-6
identification accuracy (%)
100
90
80
70
60
50
40
30
20
10
0
0 18 36 54 72 90 108 126 144 162 180
probe view angle ( 度 )
previous
ours


Gallery: NM #1-4, Probe: BG #1-2
identification accuracy (%)
100
90
80
70
60
50
40
30
20
10
0
0 18 36 54 72 90 108 126 144 162 180
probe view angle ( 度 )


Gallery: NM #1-4, Probe: CL #1-2
identification accuracy (%)
100
90
80
70
60
50
40
30
20
10
0
0 18 36 54 72 90 108 126 144 162 180
probe view angle ( 度 )

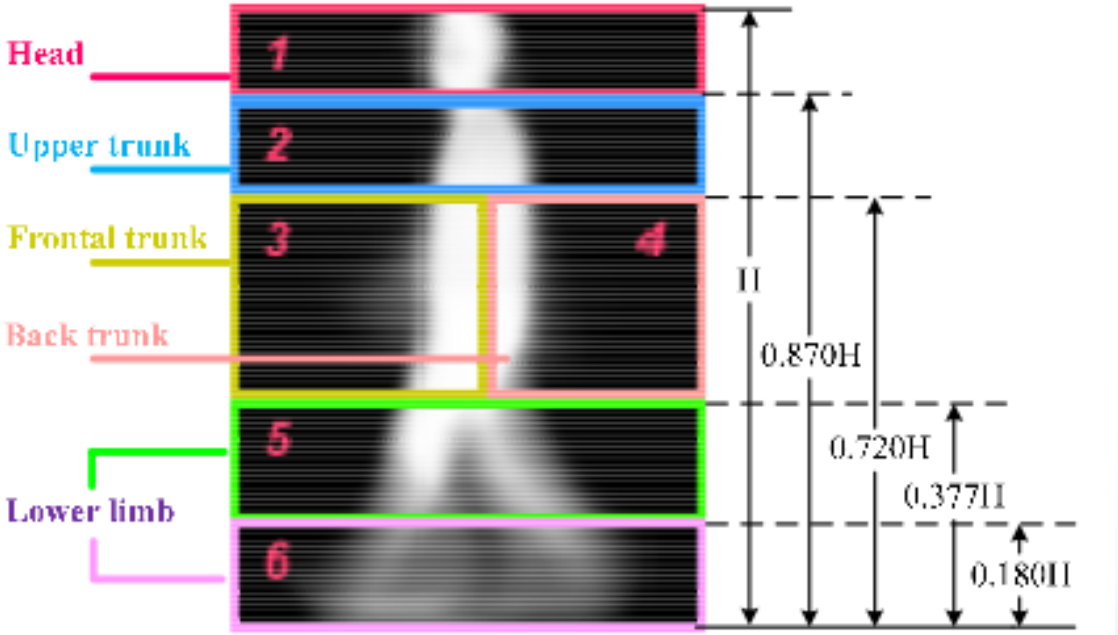
# --> 拓展

Gait Entropy Image (GEnI):



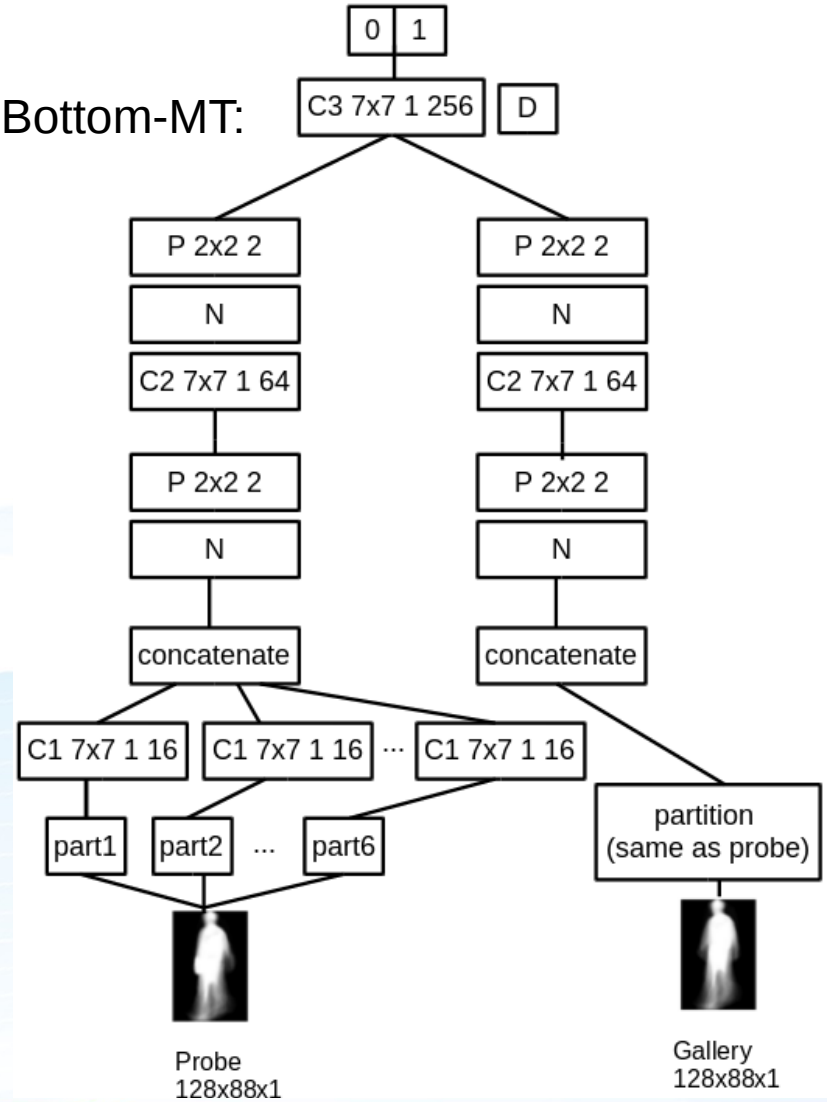
# --> 拓展

分块:

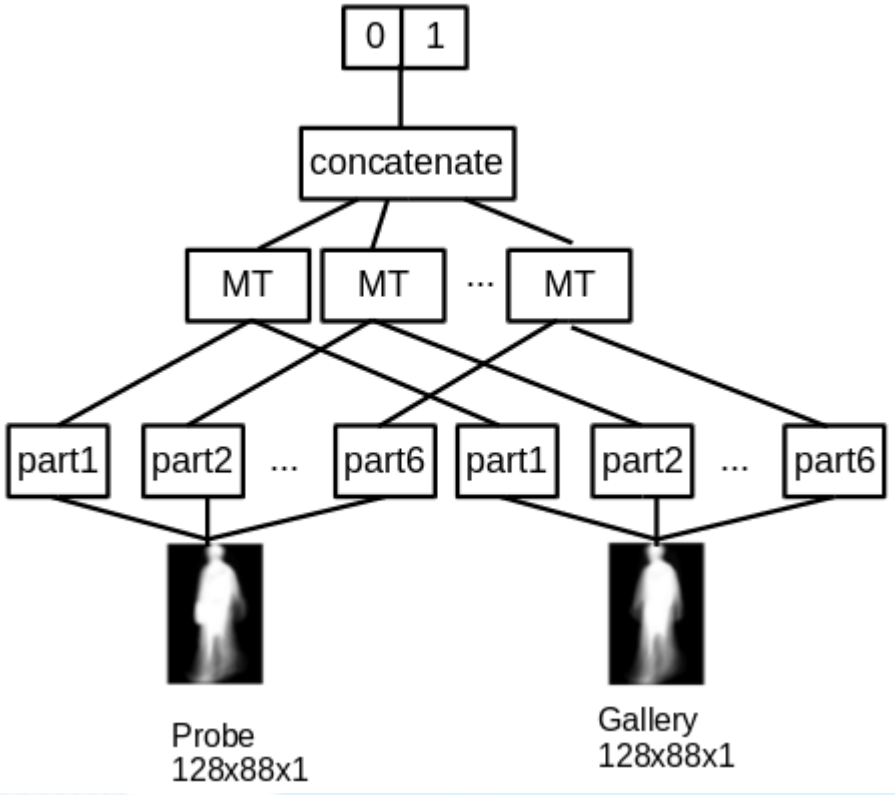

Head
Upper trunk
Frontal trunk
Back trunk
Lower limb
1
2
3
4
5
6
H
0.870H
0.720H
0.377H
0.180H

# --> 拓展

Bottom-MT:



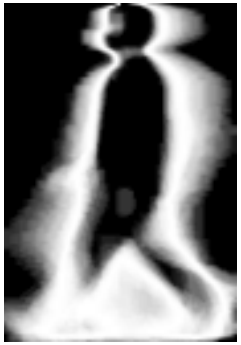

Top-MT:



# --> 总结与展望

| | 平均准确率 | | |
|---|---|---|---|
| | 正常 | 带包 | 穿大衣 |
| Z. Wu’s | 91.1% | 73.3% | 50.9% |
| Ours | 95.8% | 91.5% | 84.4% |
| GEnI | 94.7% | 88.7% | 84.0% |
| Bottom-MT | 95.7% | 90.2% | 84.1% |
| Top-MT | 95.6% | 87.1% | 80.2% |

# --> 总结与展望



**提高图片的精确程度：**

- 改进背景删除算法
- 改进人体居中算法

**利用步态序列中的时序信息：**

- 采用 RNN ／ LSTM 提取时间信息
- 采用色彩步态轮廓图或者光流图等带有时序信息的方式来描述步态

# --> 参考文献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# 谢谢！
# Q&A

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