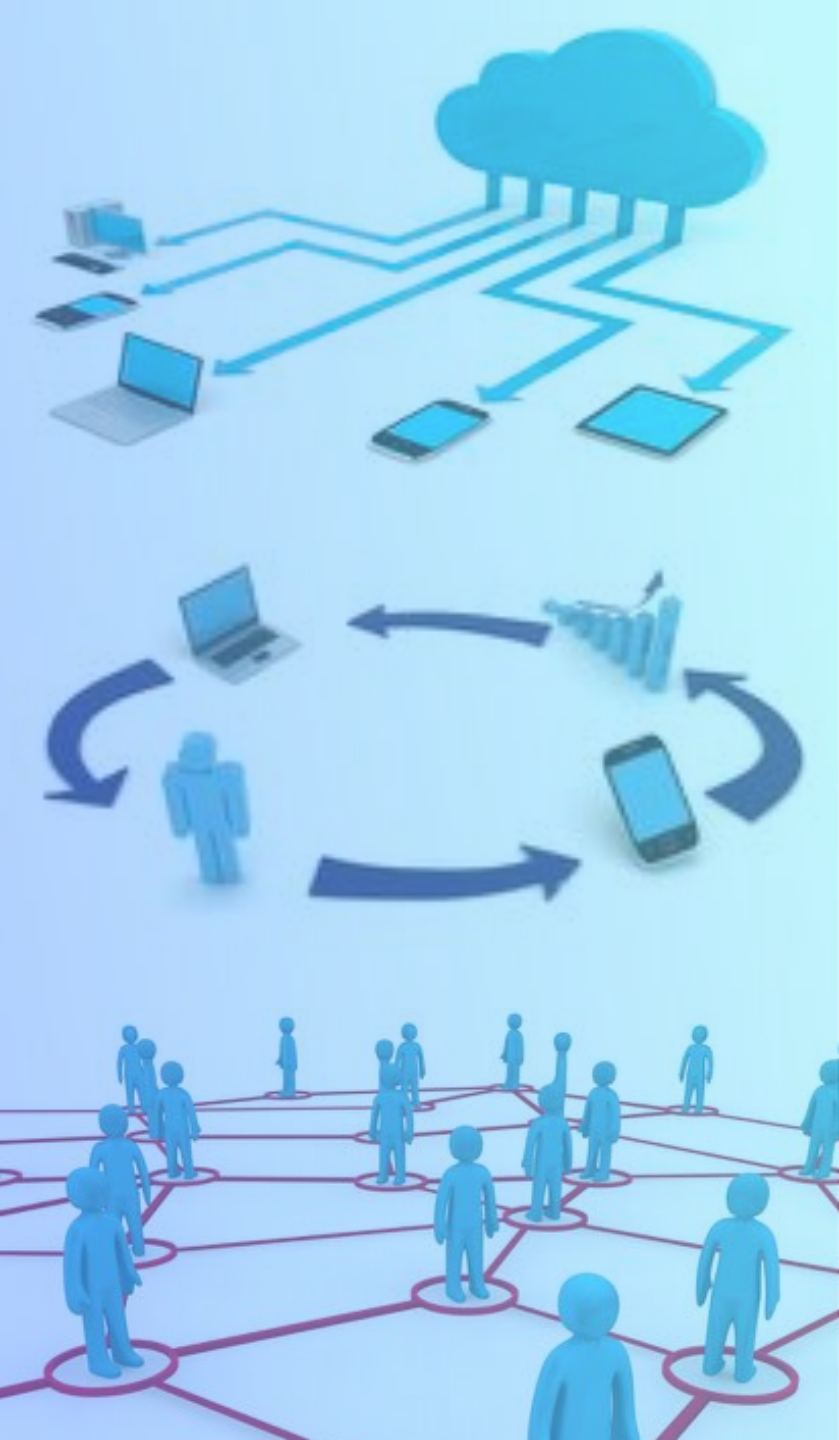


第二篇 感知模态

第2章 传感器感知技术

《智能感知技术导论》



目录

1

视觉感知技术

2

语音感知技术

3

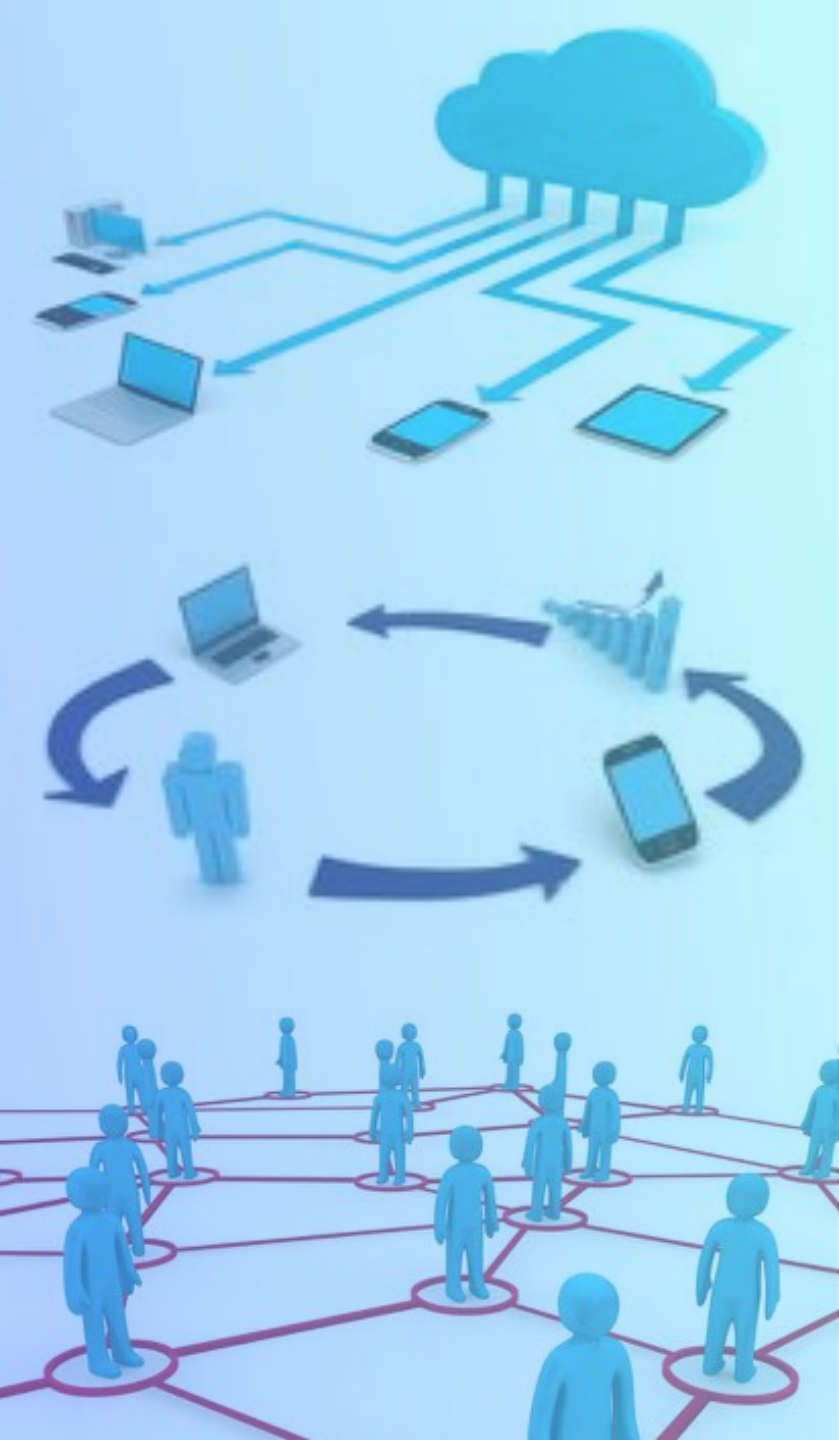
触屏感知技术

4

惯性感知技术

5

其他感知技术

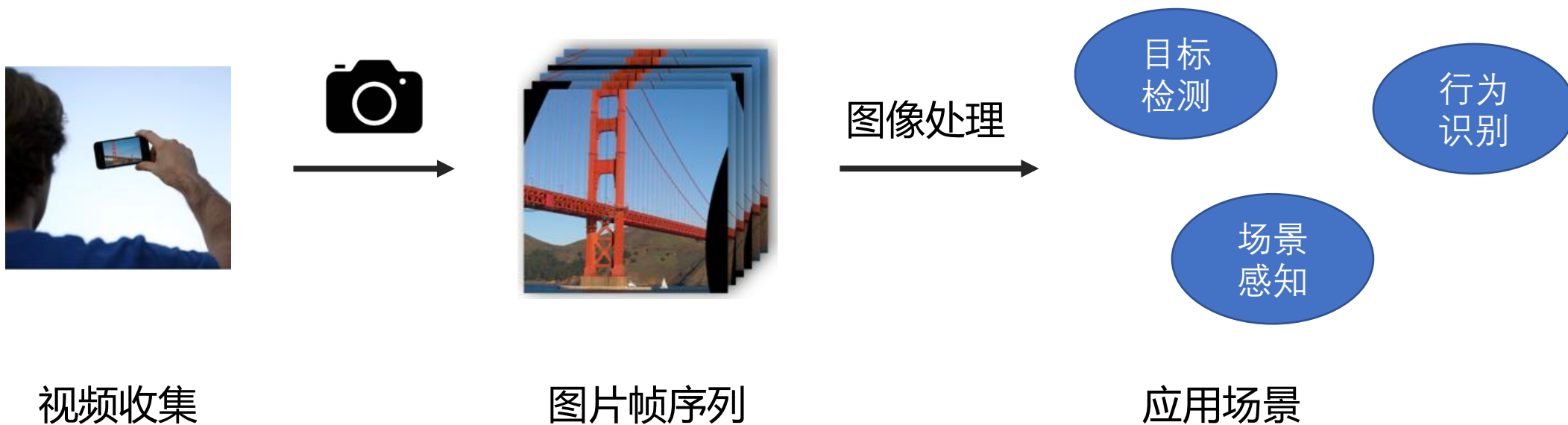


PART.1

视觉感知技术

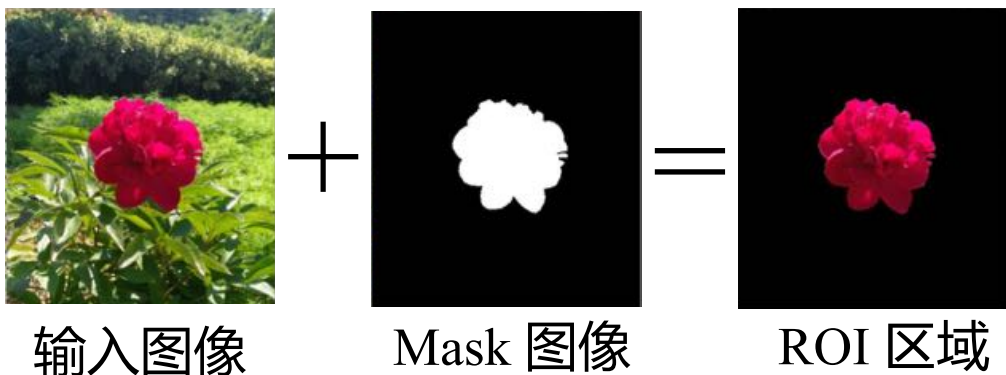
基本原理

- 视觉感知是对图像或视频数据中的目标、行为、场景等信息进行识别、测量和理解的过程，用于目标检测、行为识别、场景感知等。

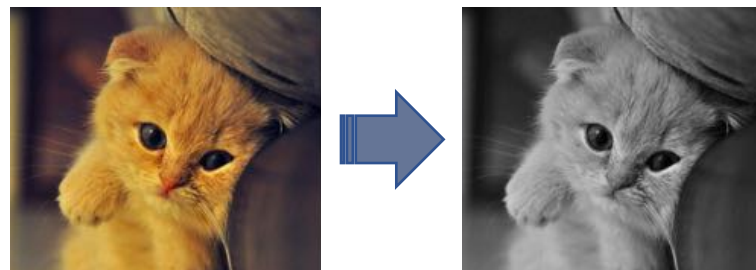


典型的数据预处理方法

- ROI 提取：设置感兴趣区域



- 灰度化：像素点为0-255的灰度值



$$Gray = \sqrt[2.2]{\frac{R^{2.2} + (1.5G)^{2.2} + (0.6B)^{2.2}}{1 + 1.5^{2.2} + 0.6^{2.2}}}$$

- 通道分离：RGB三通道分离

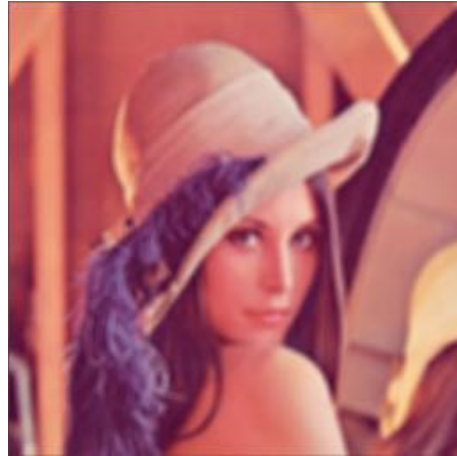


典型的数据预处理方法

- 滤波：简单常用的图像处理方法，主要用于减少噪点或失真
 - 线性滤波：方框滤波、均值滤波、高斯滤波等
 - 非线性滤波：中值滤波、双边滤波等
 - 形态学滤波：腐蚀、膨胀、开/闭运算等



输入图像



均值滤波

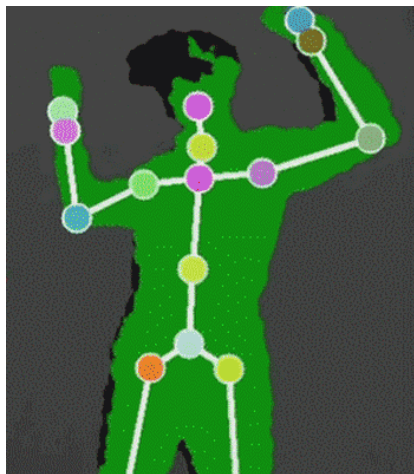


形态学腐蚀

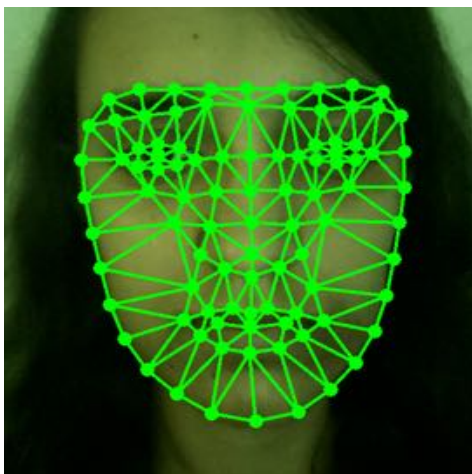


形态学膨胀

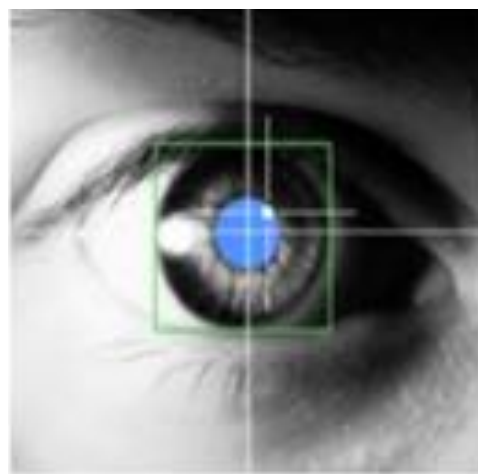
研究进展



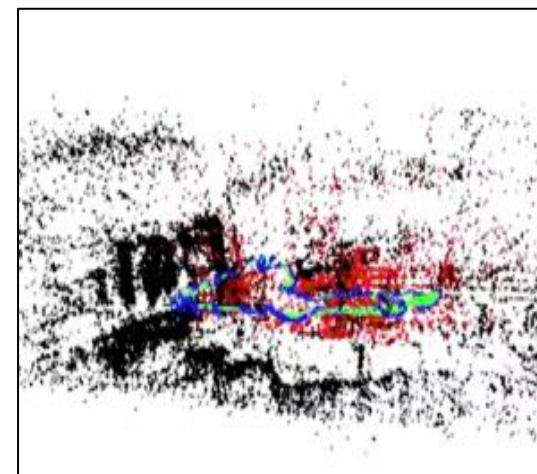
目标检测



人脸识别 [1]



眼球追踪 [2]



三维重建 [3]

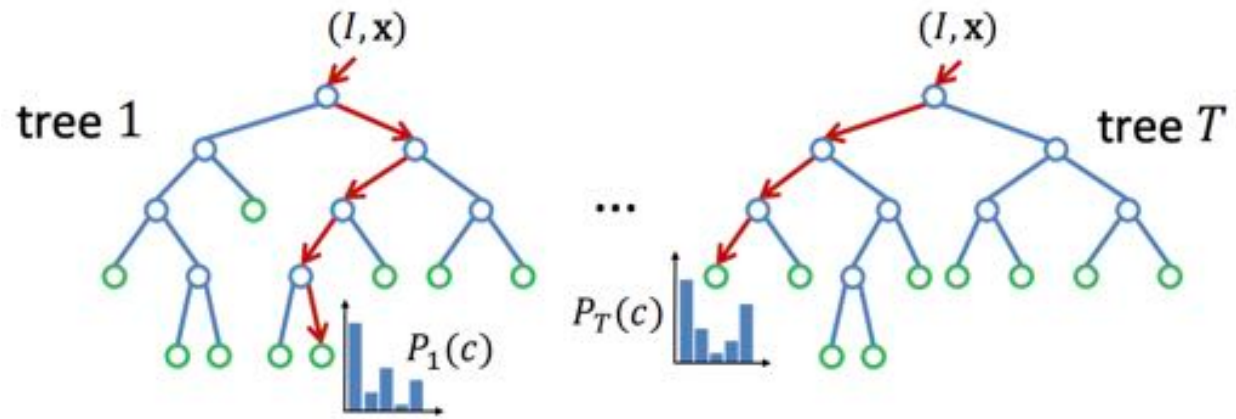
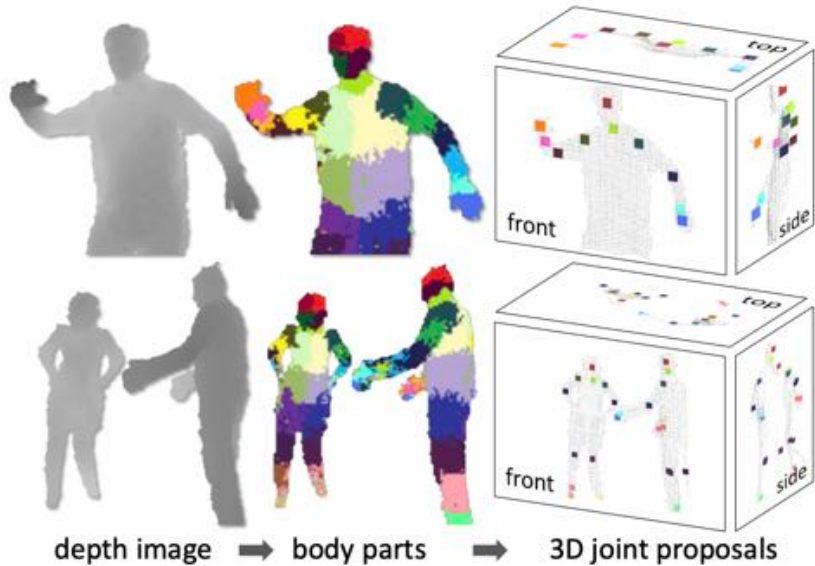
[1] Farrukh, H., Aburas, R. M., Cao, S., Wang, H. “FaceRevelio: a face liveness detection system for smartphones with a single front camera”. ACM MobiCom, 2020.

[2] Song, C., Wang, A., Ren, K., Xu, W. “Eyeveri: A secure and usable approach for smartphone user authentication”. IEEE, INFOCOM. 2016.

[3] https://github.com/raulmur/ORB_SLAM2.

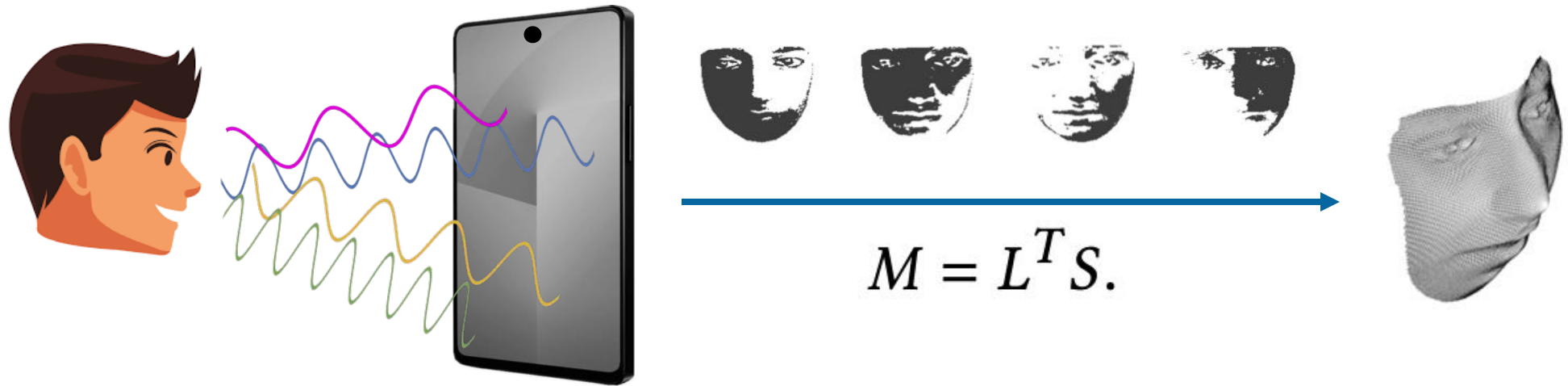
研究进展——人体关节点检测

- 从单张深度图中预测人体关节的3D位置，设计一种身体部位的**中间表示形式**，将姿势估计问题映射为像素分类问题，然后采用**随机森林**分类器识别身体部位，重新投影生成人体关节。



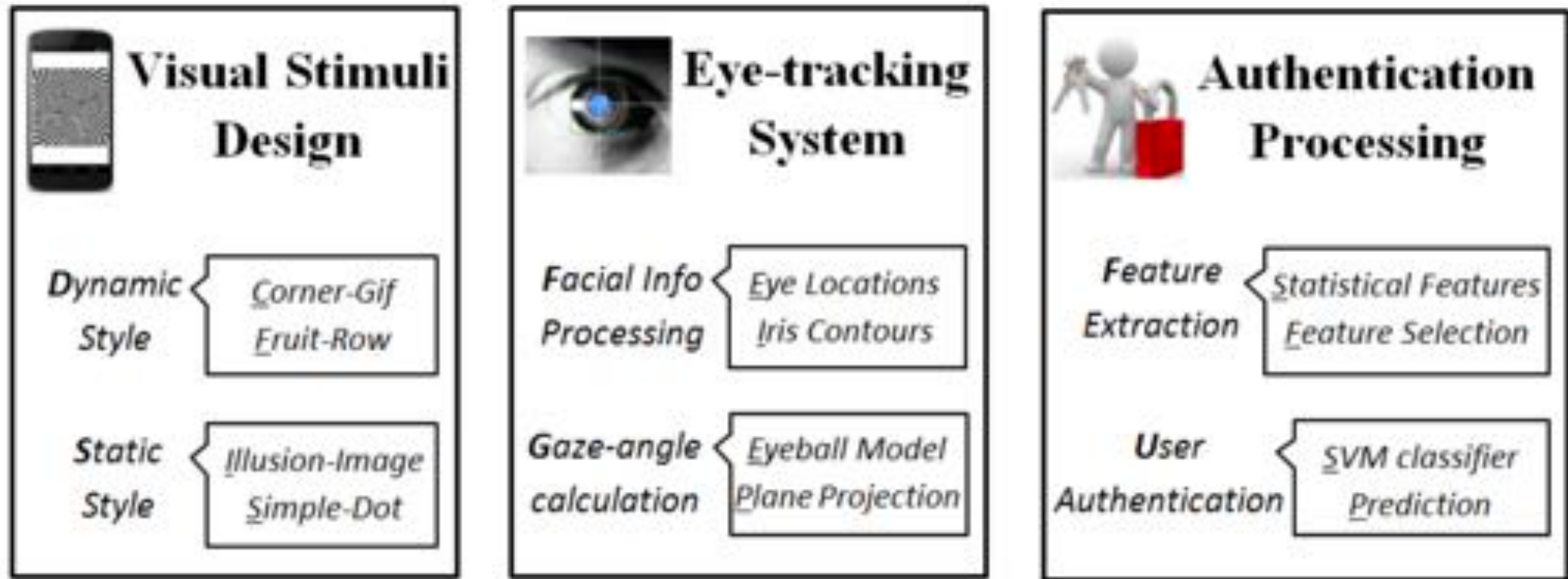
研究进展——3D人脸识别

- 利用智能手机屏幕从多个方向照亮用户的脸部，捕获不同光照下的面部图像通过光度立体恢复面部表面，并将其整合为3D面部轮廓，以实现3D人脸识别、避免2D模仿攻击



研究进展——眼球追踪

- 基于眼球追踪的移动设备身份验证系统，通过前置摄像头跟踪人眼的运动，并应用信号处理和模式匹配技术来验证用户身份

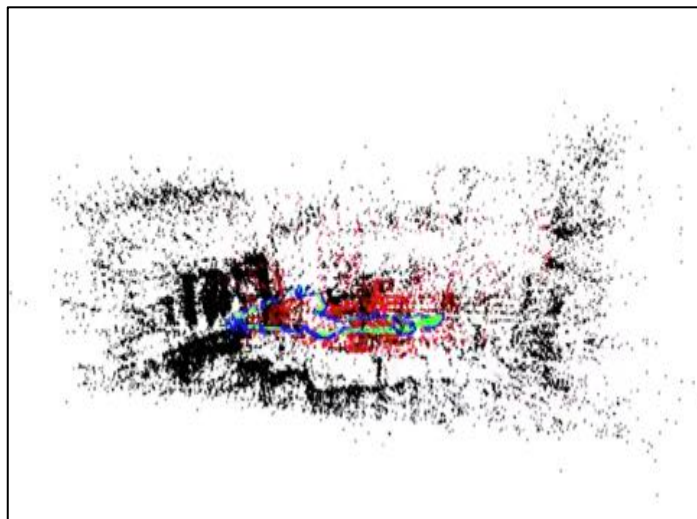


研究进展——三维重建

- 通过多视角二维图像帧序列感知还原三维场景，通过**稀疏重建**过程匹配特征点、计算三维稀疏点云、估计相机参数，然后利用**稠密重建**过程计算相机位姿、逐像素点计算密集空间点云



稀疏重建



稠密重建



重建结果

[1] https://github.com/raulmur/ORB_SLAM2.

典型案例——基于移动设备内置摄像头的文本输入技术

- 如何基于内置摄像头**实时准确地**向移动设备输入文本？



iPad mini



iPhone



Apple Watch



Google Glass



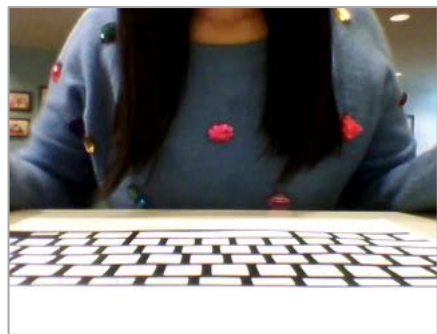
屏幕越来越小 → 文本输入愈发低效

- 小屏移动设备的前置摄像头
- 一张纸质布局

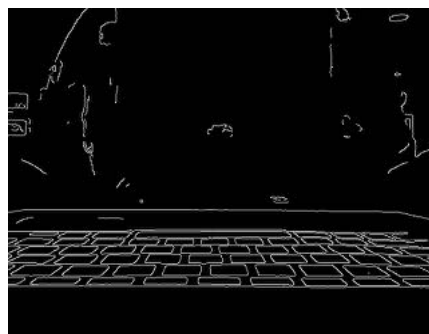
→ 自然高效的实时文本输入体验

典型案例——基于移动设备内置摄像头的文本输入技术

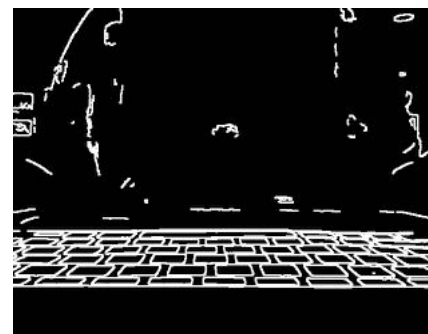
- 按键提取：通过 Canny 边缘检测和 Hough 变换检测键盘的边缘直线，然后利用颜色分割和按键面积特征分离出按键轮廓，并映射到对应字符



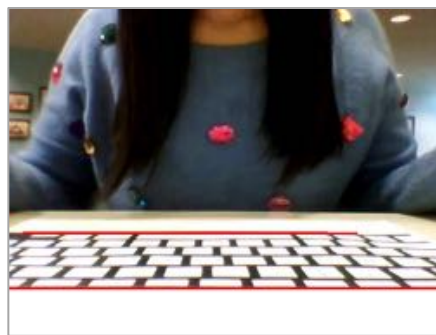
(a) An input image



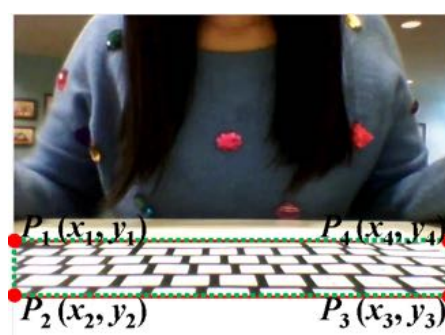
(b) Canny edge detection result



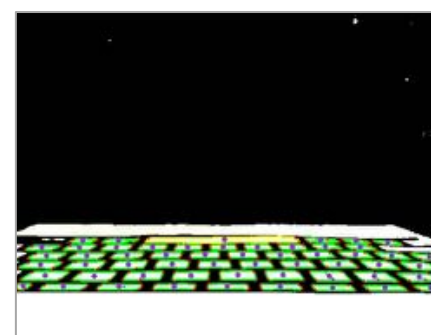
(c) Optimization for edges



(d) Position range of keyboard



(e) Keyboard boundary



(f) Key Segmentation Result

典型案例——基于移动设备内置摄像头的文本输入技术

- 指尖检测：结合 Otsu 方法和YCrCb空间的Cr分量分割手部，利用指尖的形状特征检测指尖



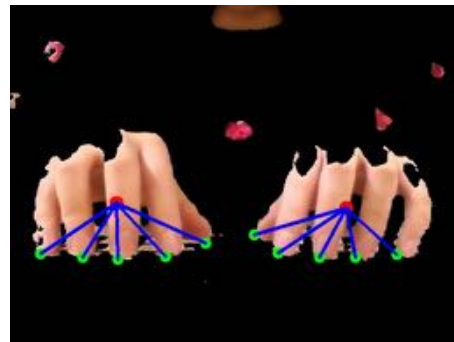
(a) An input image



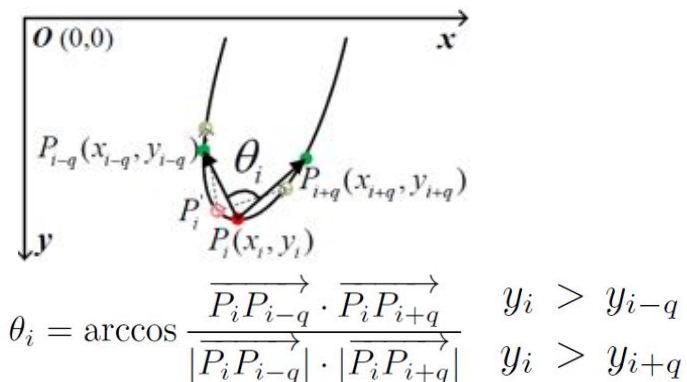
(b) Hand Segmentation



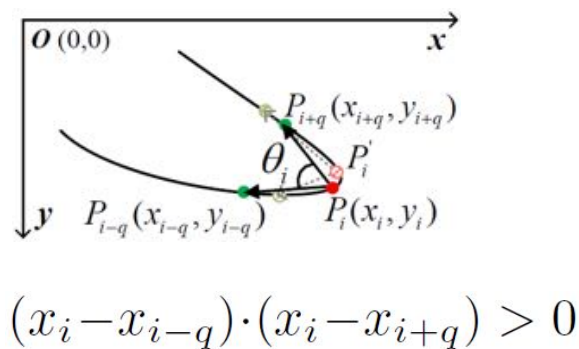
(c) Finger's contour



(d) Fingertips



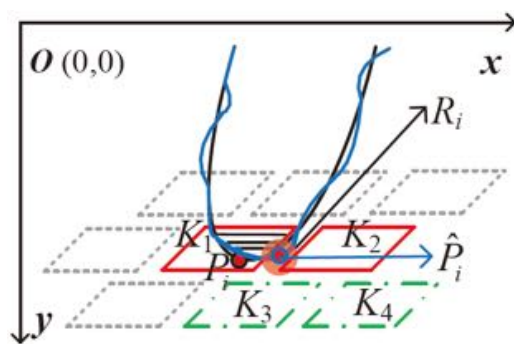
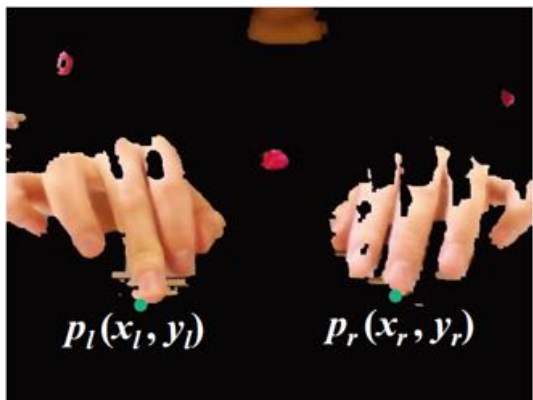
- Fingertips (excluding thumbs)



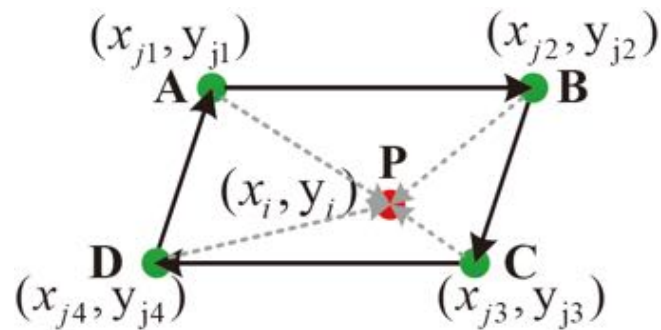
- Thumbs

典型案例——基于移动设备内置摄像头的文本输入技术

- 按键动作检测和定位：判断按键指尖是否移动来检测可能的按键动作，通过指尖与按键的距离和覆盖率定位按下的字符



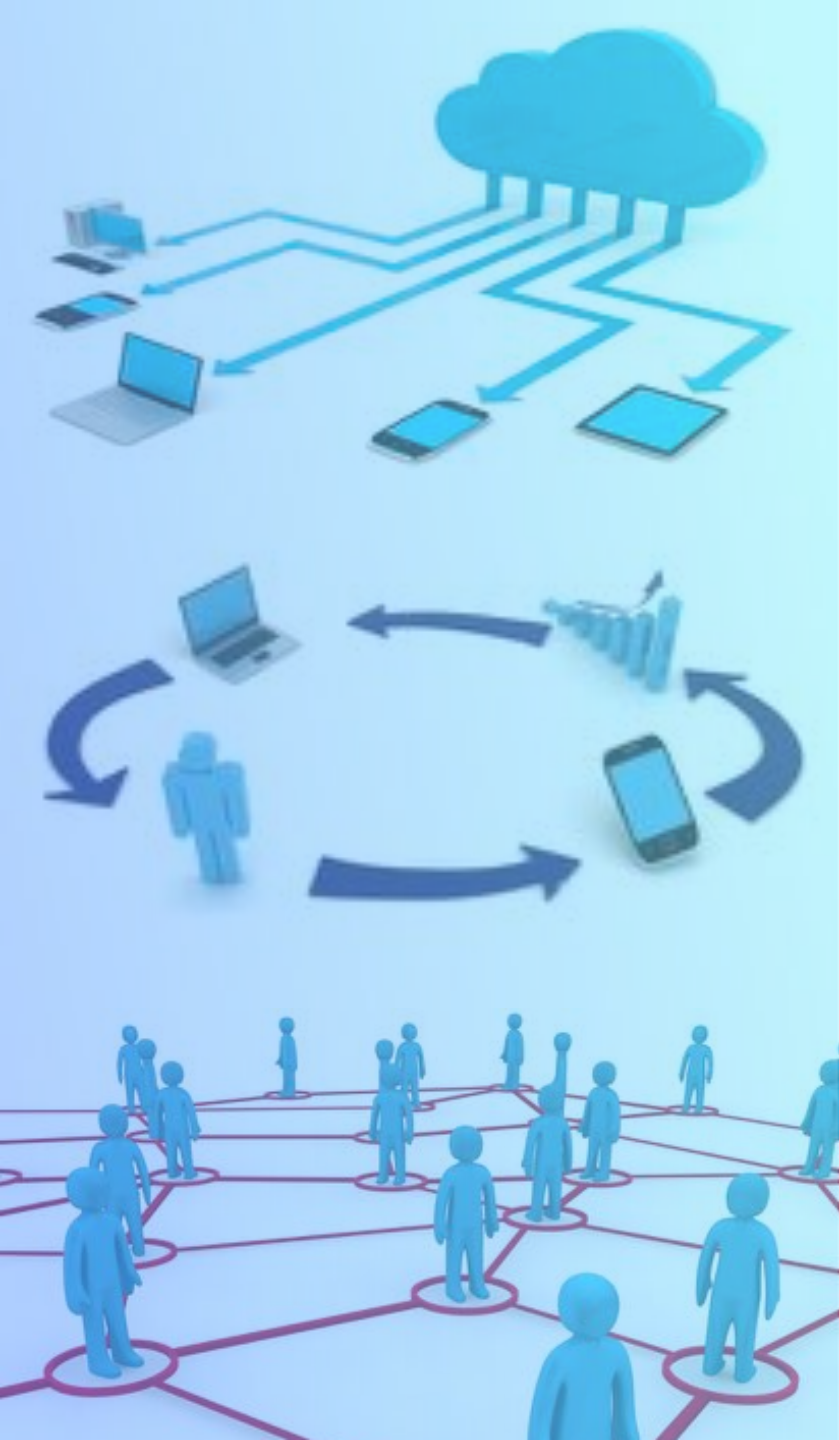
(a) Candidate keys



(b) Locating a fingertip

$$\sqrt{(x_{l_i} - x_{l_{i-1}})^2 + (y_{l_i} - y_{l_{i-1}})^2} \leq \Delta r,$$
$$\sqrt{(x_{r_i} - x_{r_{i-1}})^2 + (y_{r_i} - y_{r_{i-1}})^2} \leq \Delta r.$$

$$\vec{AB} \times \vec{AP} \geq 0, \vec{BC} \times \vec{BP} \geq 0,$$
$$\vec{CD} \times \vec{CP} \geq 0, \vec{DA} \times \vec{DP} \geq 0.$$

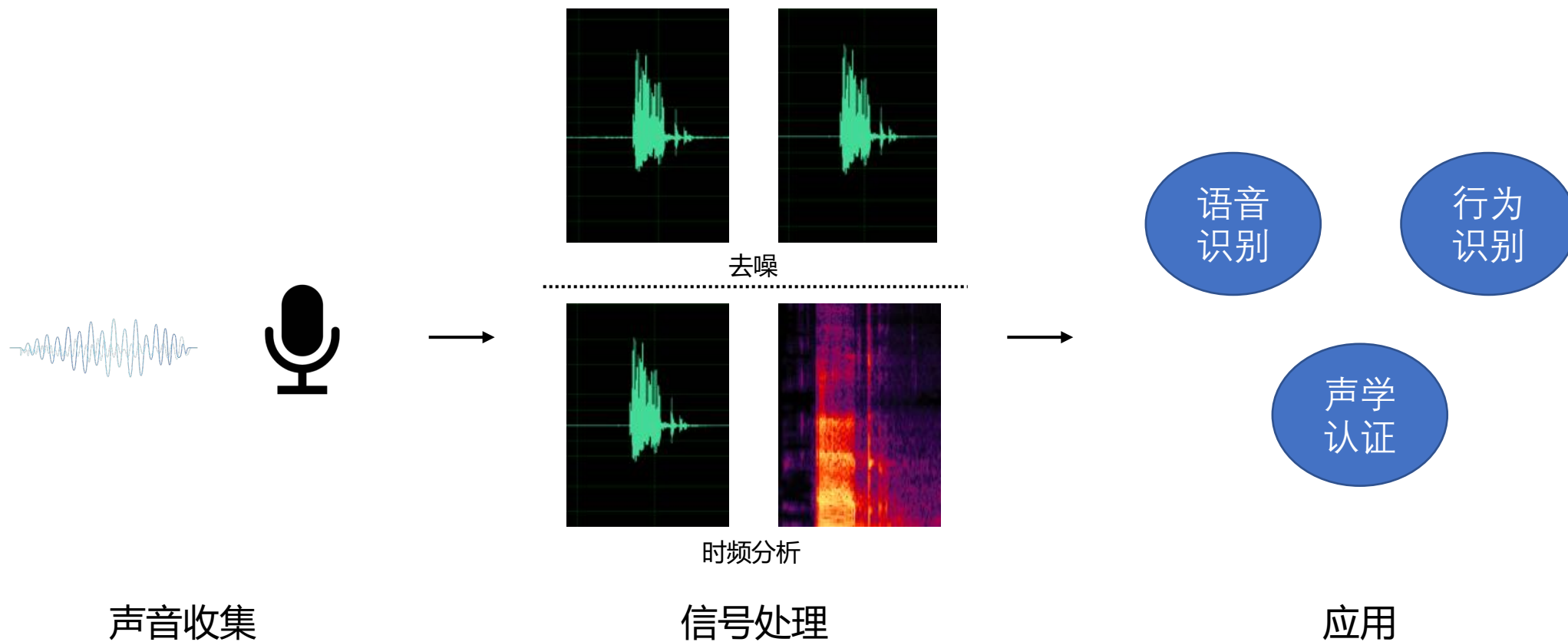


PART.2

语音感知技术

基本原理

- 语音感知是使用设备获取目标对象发出的声学信号，通过对信号进行分析处理，实现语音识别、行为识别、声学认证等功能。

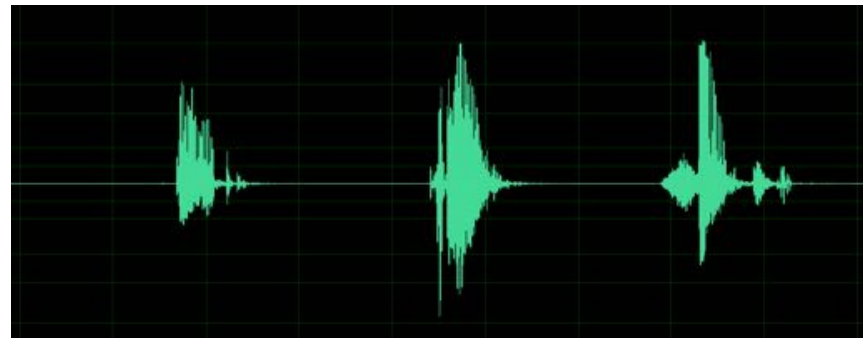


基本原理——信号处理

- 去噪

- 方法：

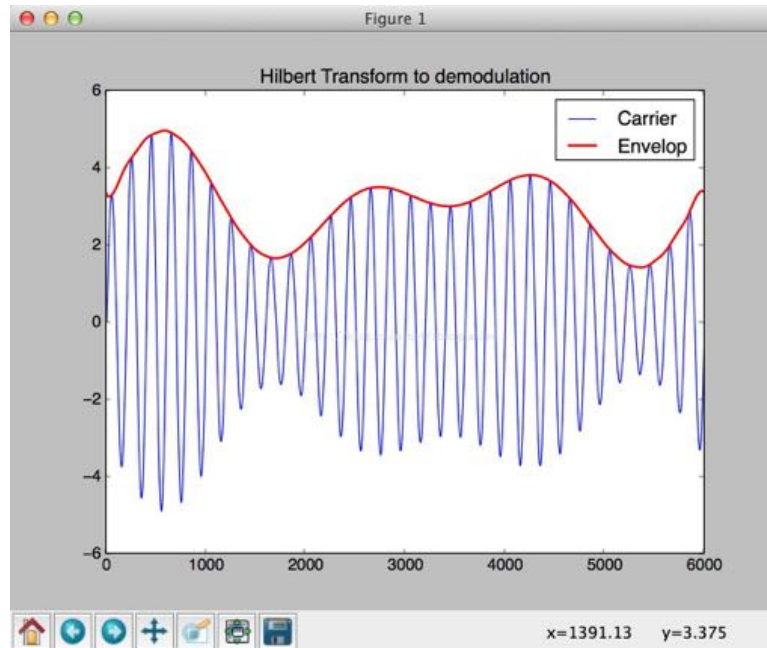
- 谱减法：取一段只有噪音的信号作为样本，在整个信号中减去这个样本
 - 滤波法：在已知目标信号的频域区段，且噪音信号和目标信号无干扰时可以在频域上通过滤波得到纯净的目标信号
 - 子空间降噪：假设语音子空间和噪声子空间正交，通过特征分解得到语音子空间的信号



谱减法

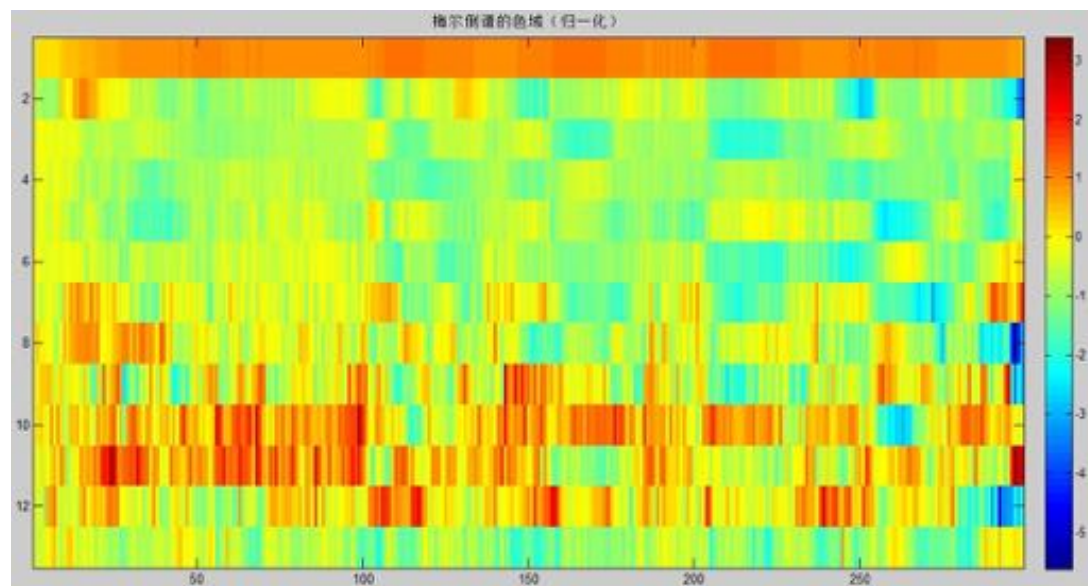
基本原理——信号处理

- 时域分析
 - 统计特征
 - 过零率，平均值，标准差，时间间隔，振幅大小等
 - 信号包络



基本原理——信号处理

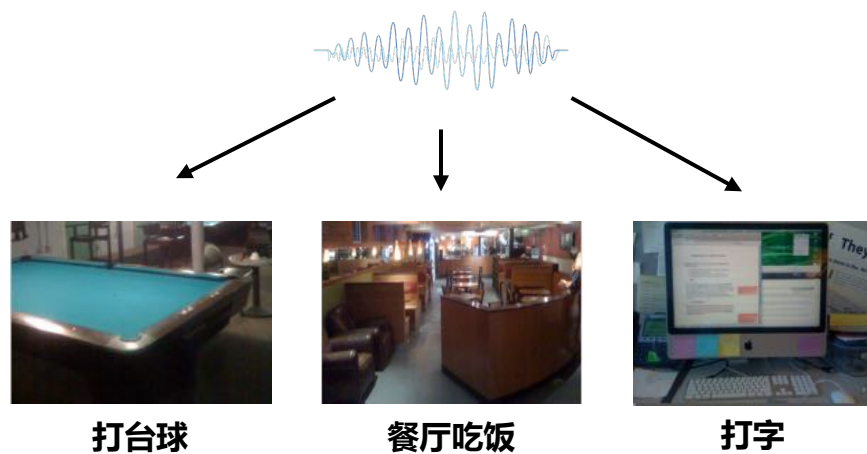
- 频域分析
 - 统计特征
 - 频带带宽，频带能量，主要频率区间
 - Mel频率倒谱系数 (MFCC)



研究进展



语音识别



行为识别 [1]

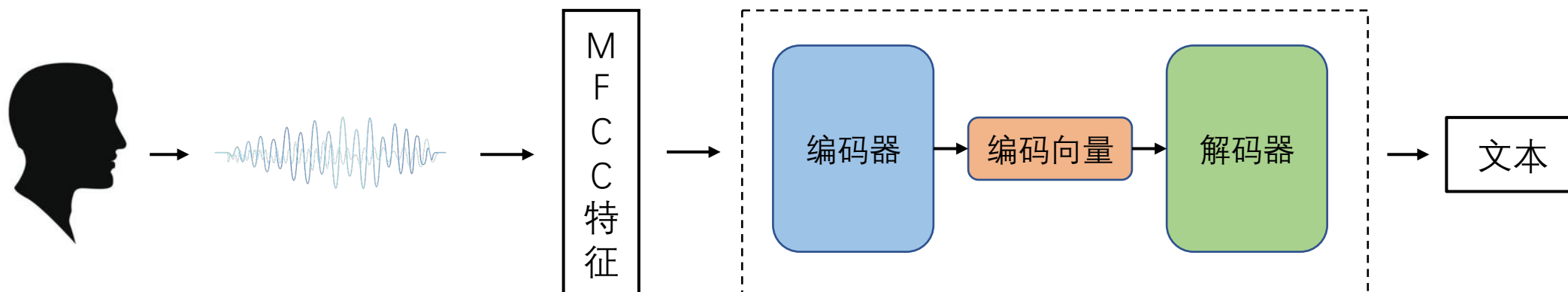


声学认证

[1] Lu H, Pan W, Lane N D, et al. Soundsense: scalable sound sensing for people-centric applications on mobile phones[C]//Proceedings of the 7th international conference on Mobile systems, applications, and services. 2009: 165-178.

研究进展——语音识别

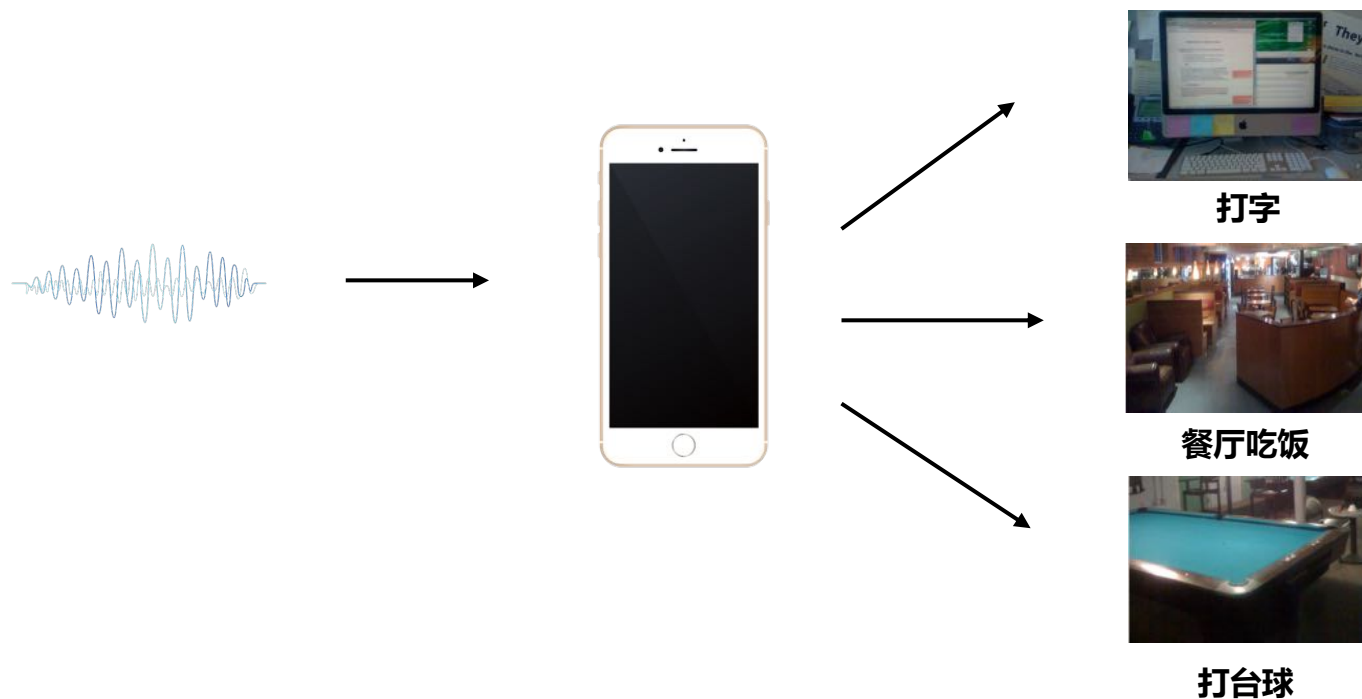
- 语音识别：从句子级别的语音信号中提取MFCC特征，使用端到端的深度学习网络将特征翻译成文本。



[1] Chan W, Jaitly N, Le Q, et al. Listen, attend and spell: A neural network for large vocabulary conversational speech recognition[C]//2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2016: 4960-4964.

研究进展——行为识别

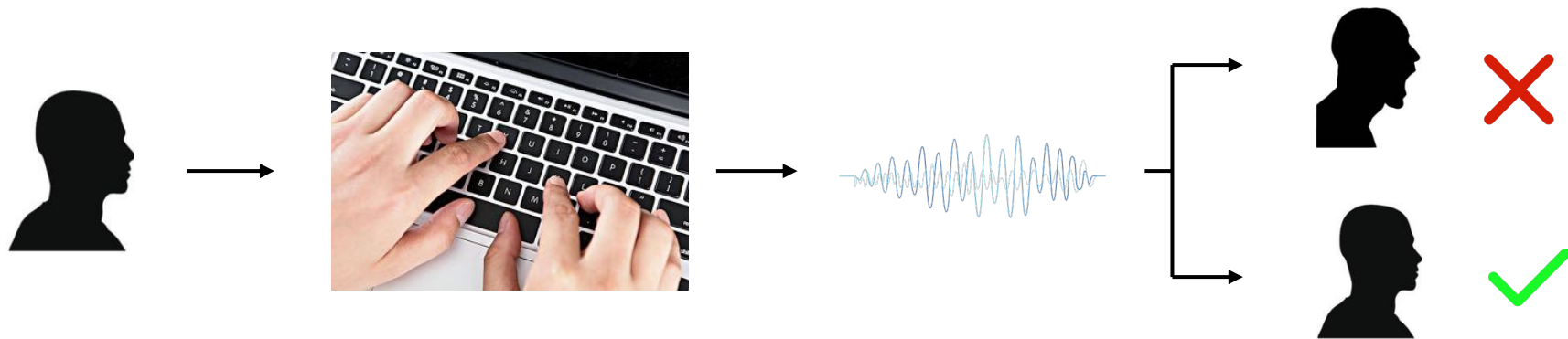
- 声音事件识别：使用手机麦克风收集声音，从收集到的声音信号中提取时域和频域上的特征，使用两阶段分类对声音事件进行识别，即先将声音分成几种大类，之后对从大类中分出小类。



[1] Lu H, Pan W, Lane N D, et al. Soundsense: scalable sound sensing for people-centric applications on mobile phones[C]//Proceedings of the 7th international conference on Mobile systems, applications, and services. 2009: 165-178.

研究进展——声学认证

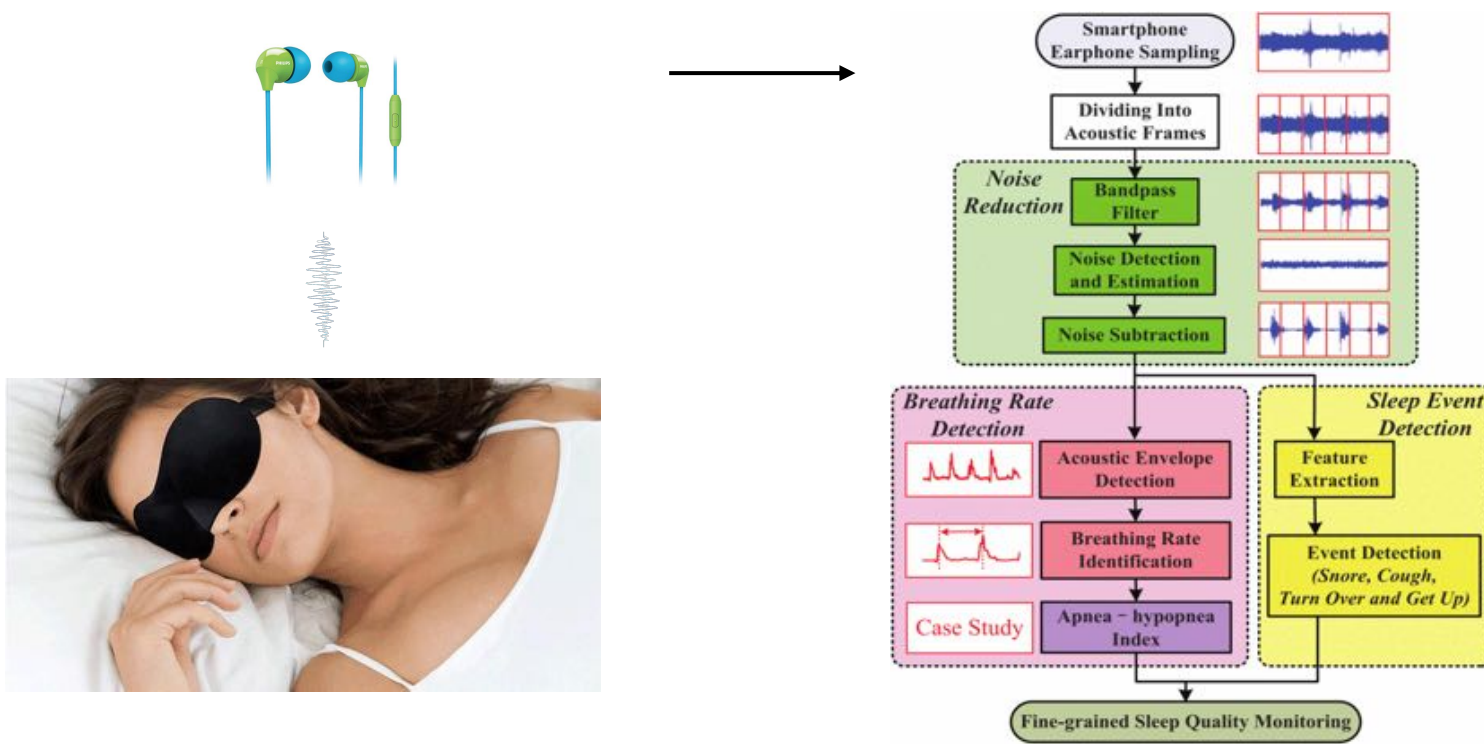
- 按键认证：使用笔记本麦克风收集按键声音，对信号在时域和频域上提取特征，将特征输入到C-SVC分类器中进行认证。



[1] Zhou Q, Yang Y, Hong F, et al. User identification and authentication using keystroke dynamics with acoustic signal[C]//2016 12th International Conference on Mobile Ad-Hoc and Sensor Networks (MSN). IEEE, 2016: 445-449.

典型案例——睡眠监测

- 使用手机耳机收集睡眠过程中的声音来分析睡眠质量

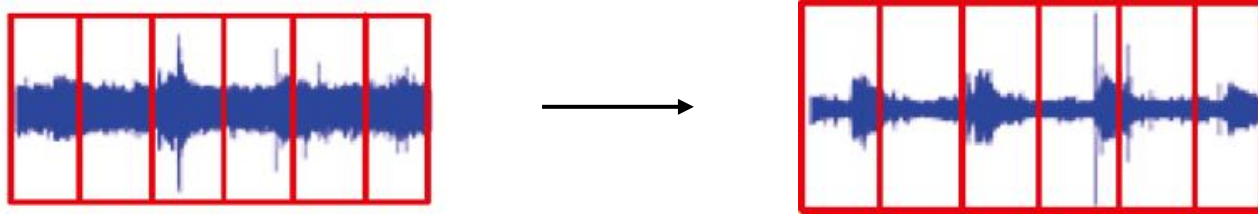


系统架构

[1] Ren Y, Wang C, Yang J, et al. Fine-grained sleep monitoring: Hearing your breathing with smartphones[C]//2015 IEEE Conference on Computer Communications (INFOCOM). IEEE, 2015: 1194-1202.

睡眠监测——降噪

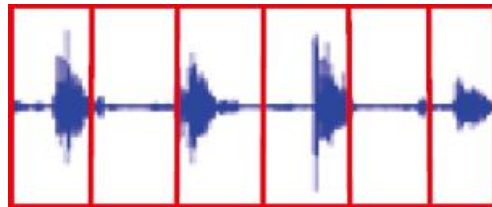
- 对收集的信号进行滤波，只保留100Hz-3400Hz之间的信号



- 对信号进行分帧，对每帧计算方差找到噪声帧片段

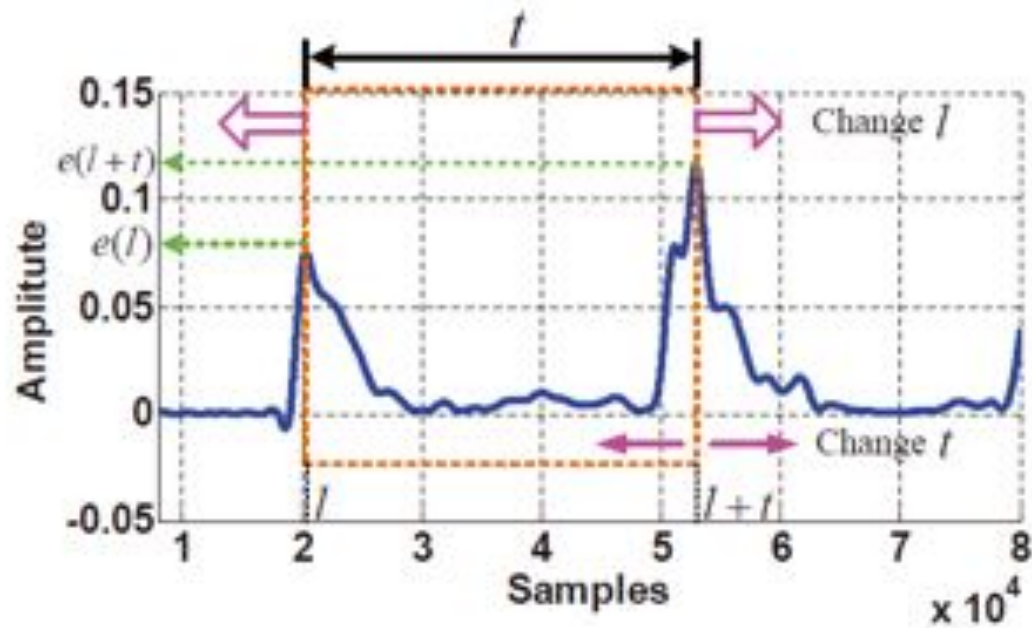


- 将滤波后的信号减去噪声信号



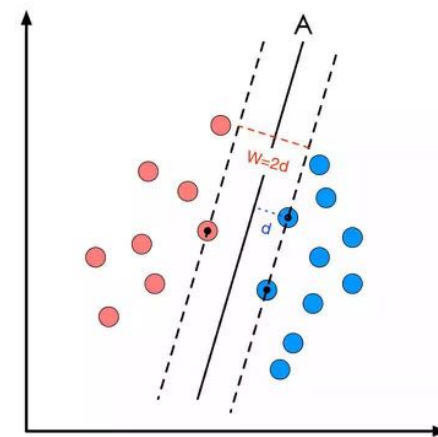
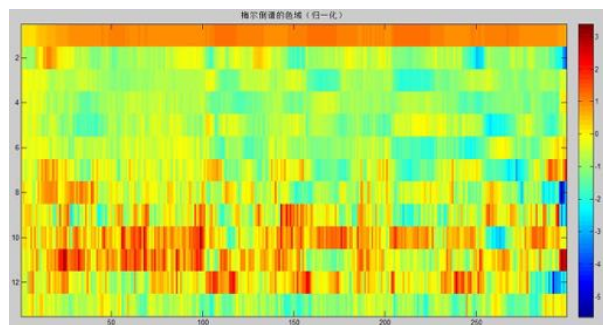
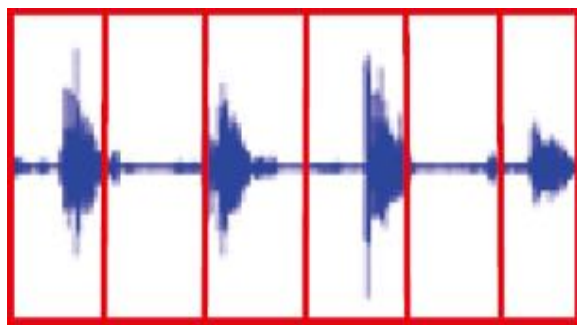
睡眠监测——呼吸频率的识别

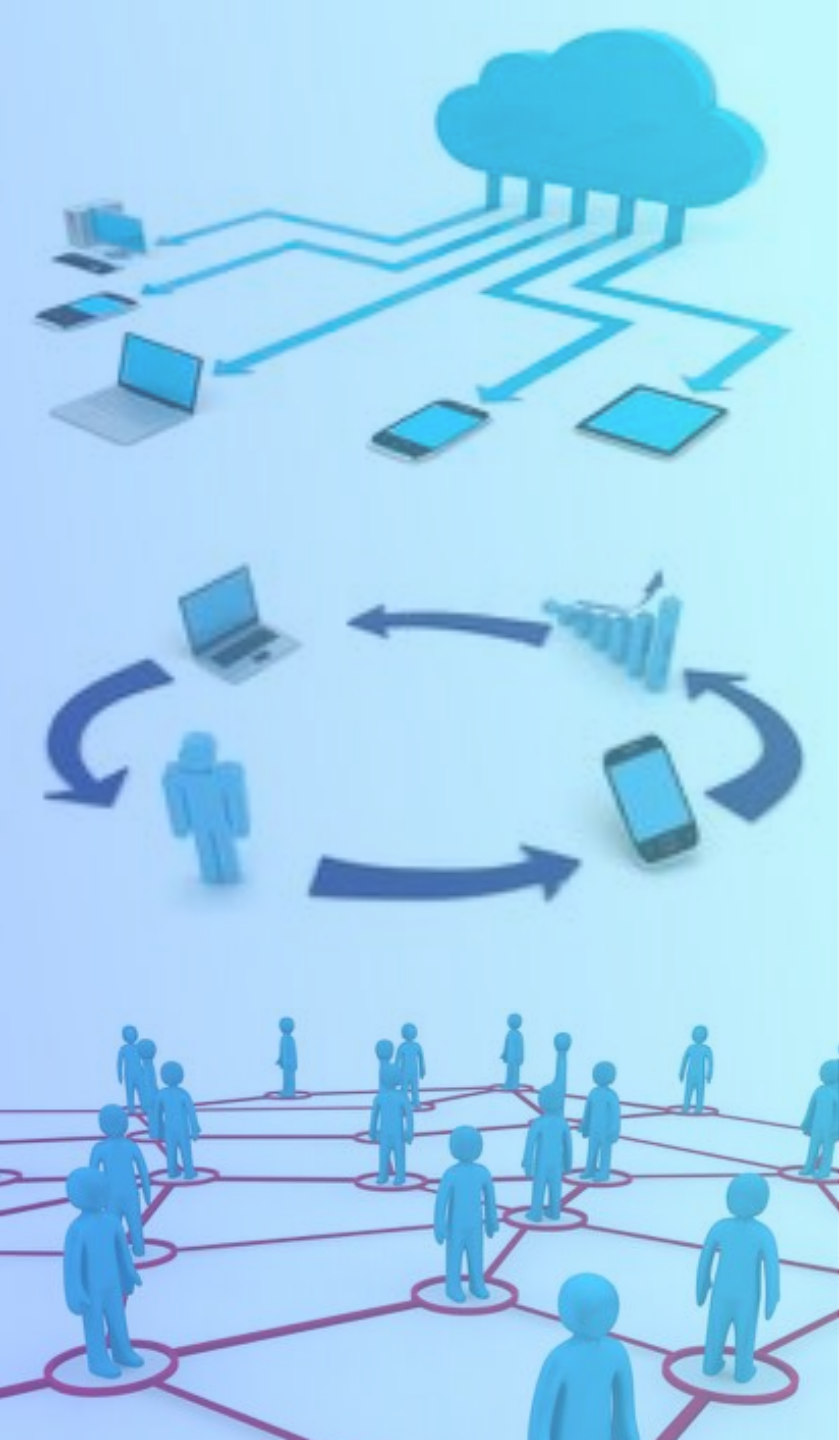
- 求出信号包络，在信号包络上找到呼吸的周期，从而可以计算呼吸频率



睡眠监测——睡眠事件分析

- 判断睡眠过程中出现了哪些事件，比如打鼾，咳嗽，翻身，起夜。具体操作是对信号的每一帧提取MFCC特征，使用SVM分类器对特征进行分类。





PART.3

触屏感知技术

背景

- 随着iPhone、iPad等的问世，触屏设备逐渐成为移动设备的主流；



- 与此同时，用户与移动手机日常的交互操作，也由原来的按键变为如今的各种触屏操作。

基本原理

- 随着触摸屏如何将物理的接触转化为坐标信号？

- 电阻式触摸屏（早期）

- 原理：按压导致屏幕电阻变化



- 缺点：需要校准；不支持多点触控

- 电容式触摸屏（常用）

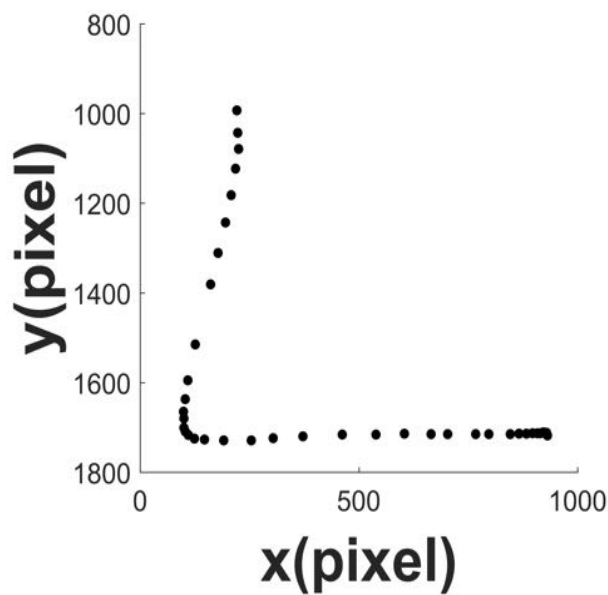
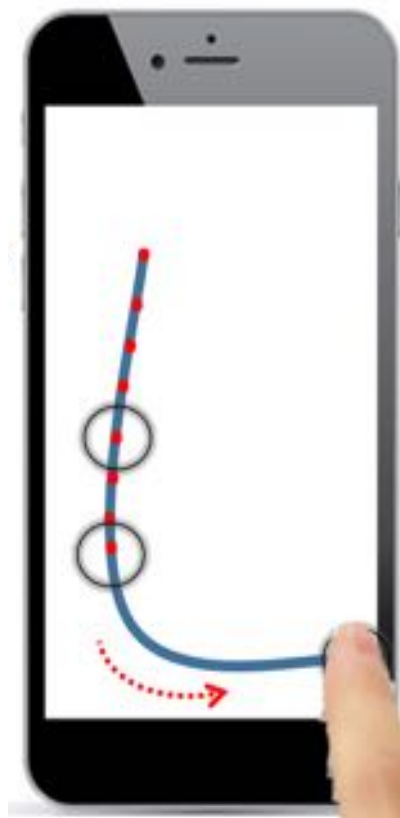
- 原理：接触时有人体电流感应现象



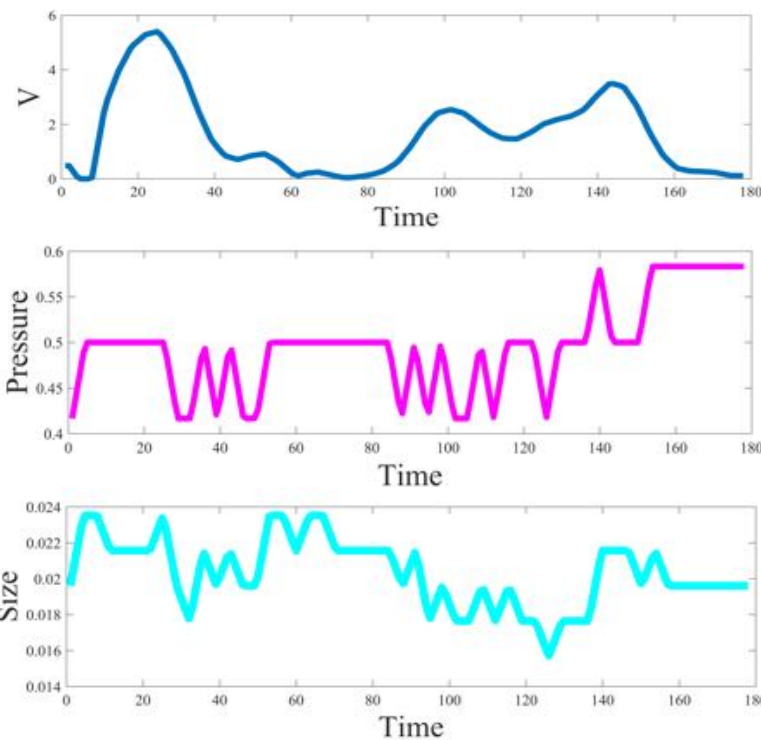
基本原理

- 触摸屏的感知粒度

- 原始数据包括坐标数据、滑动速度、按压压力、手指触摸面积
- 基于上述数据可进一步推断出滑动的加速度、滑动方向等



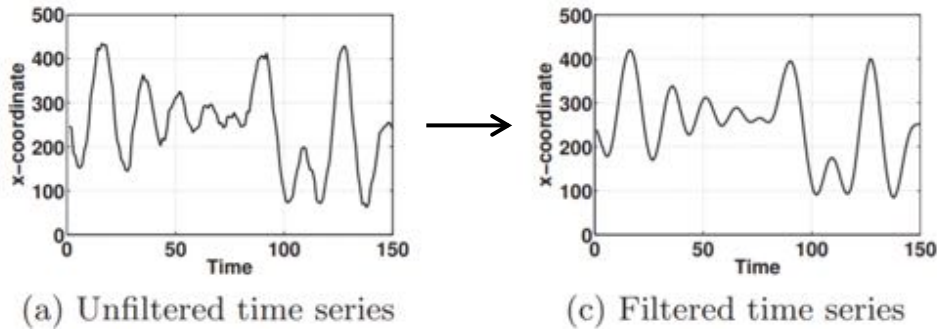
坐标数据



速度、压力、触摸面积

基本原理——典型的数据预处理方法

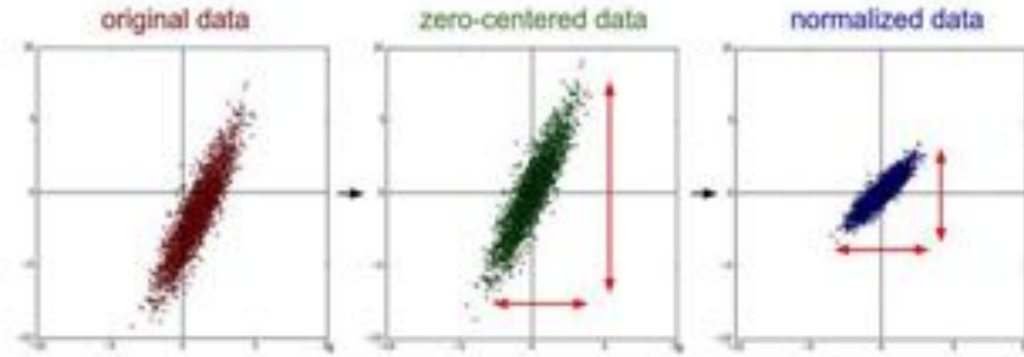
• 除去噪声



$$\hat{x}(t) = \frac{x(t) + x(t-1) + \dots + x(t-N+1)}{N}$$

使用SMA去除坐标中的高频噪声[1]

• 数据归一化



$$S(i) = \frac{S(i) - \mu_S}{\sum_{i=1}^L (S(i) - \mu_S)^2 L}$$

$$D_{F^1(i), F^2(i)} = \min\left\{\frac{|F^1(i) - F^2(i)|}{|F^1(i)|}, 2\right\}$$

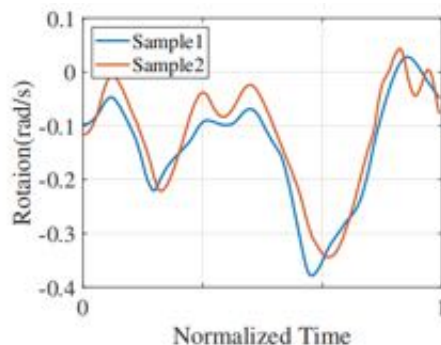
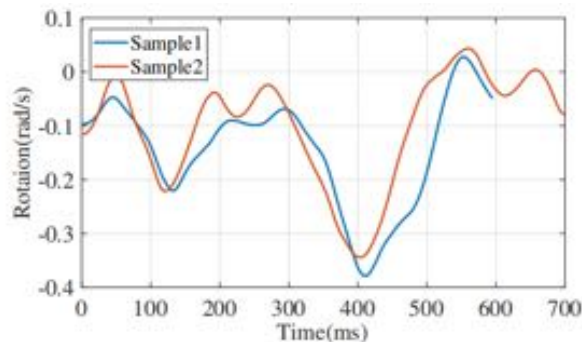
对传感器或者特征数据归一化[2]

[1] Shahzad, M., Liu, A. X., & Samuel, A. (2013). Secure unlocking of mobile touch screen devices by simple gestures - You can see it but you can not do it. Proceedings of the 19th annual international conference on Mobile computing & networking.

[2] Wang, H., Lymberopoulos, D., & Liu, A. J. (2015). Sensor-Based User Authentication.

基本原理——典型的数据预处理方法

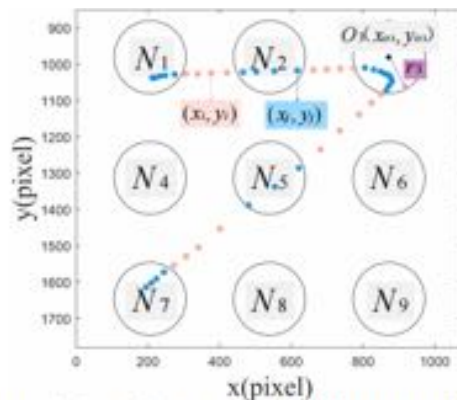
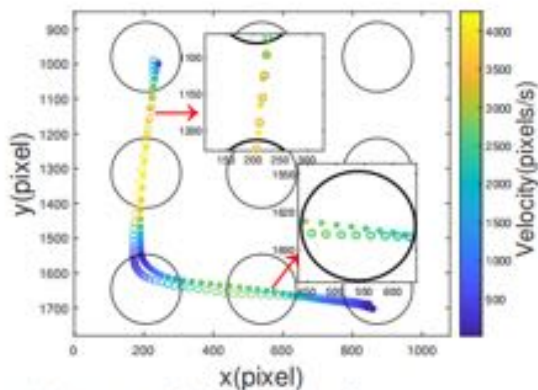
• 数据对齐



$$d'_{2k} = d_{2i} + (d_{2i+1} - d_{2i}) * (k \cdot \frac{n_2 - 1}{n_1 - 1} - i)$$

进行数据插值对齐传感器数据[1]

• 数据分割



$$\sqrt{(x_i - x_{o_k})^2 + (y_i - y_{o_k})^2} \leq r_k$$

基于坐标信息切分图案手势 [1]

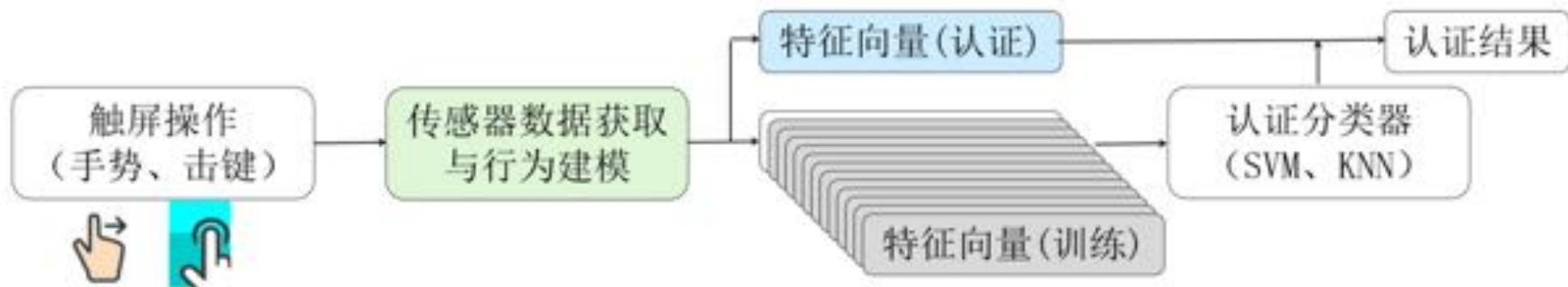
[1] Xinchun Zhang, Yafeng Yin, Lei Xie, Hao Zhang, Zefan Ge, and Sanglu Lu. 2020. TouchID: User Authentication on Mobile Devices via Inertial-Touch Gesture Analysis. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 4, 4, Article 162 (December 2020)

研究进展

- 从人机交互感知到用户身份认证感知方向演进
 - 人机交互：手势判断；键盘输入

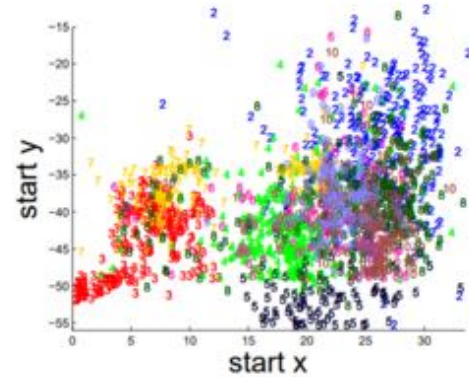
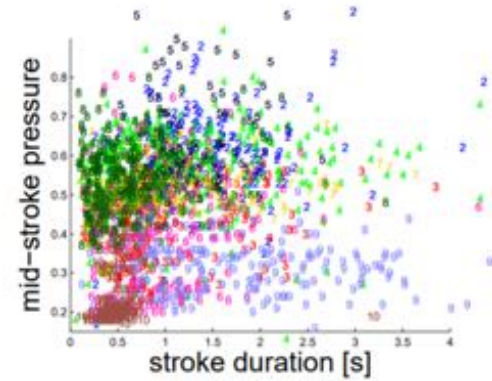
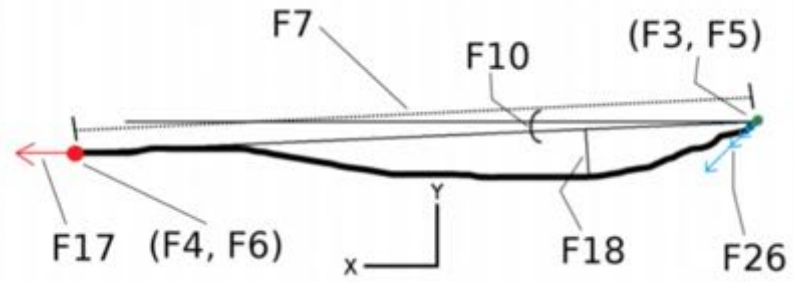
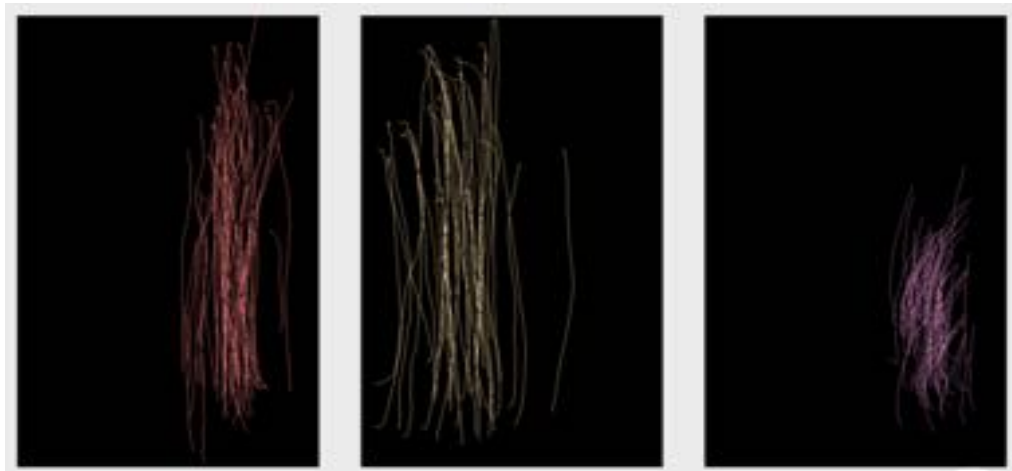


- 用户身份认证：基于用户触屏特征进行身份判断



研究进展——单指滑动的身份认证

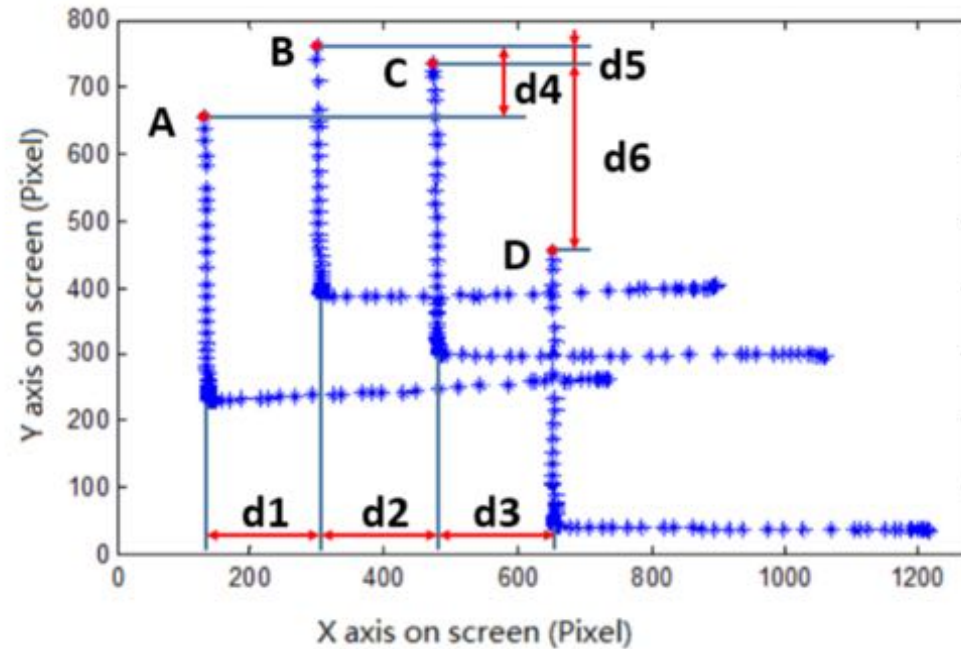
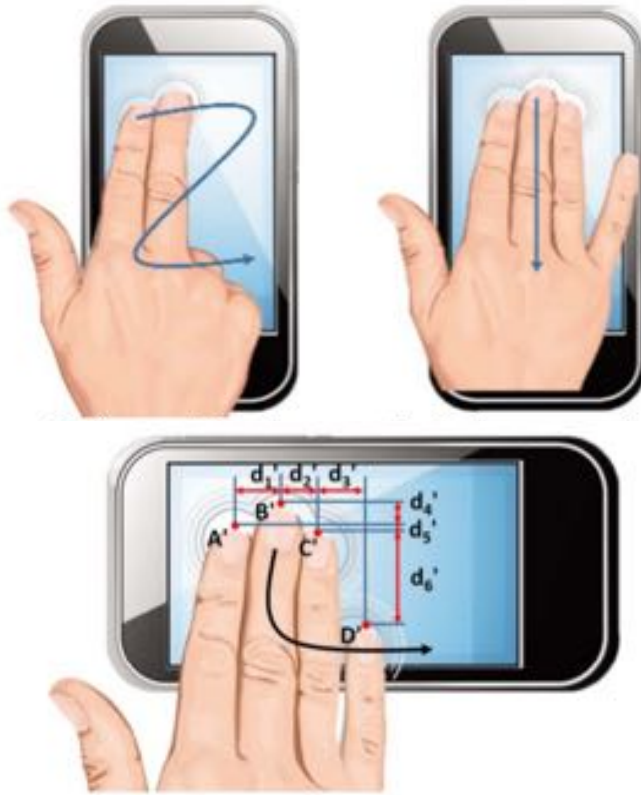
- 通过触摸屏传感器感知用户滑动手势的行为特征，如滑动速度、角度、按压面积等，再基于特征数据构建认证分类器于身份认证。



[1] Frank, M. , Biedert, R. , Ma, E. , Martinovic, I. , & D Song. (2012). Touchalytics: on the applicability of touchscreen input as a behavioral biometric for continuous authentication. IEEE Transactions on Information Forensics and Security, 8(1), 136-148.

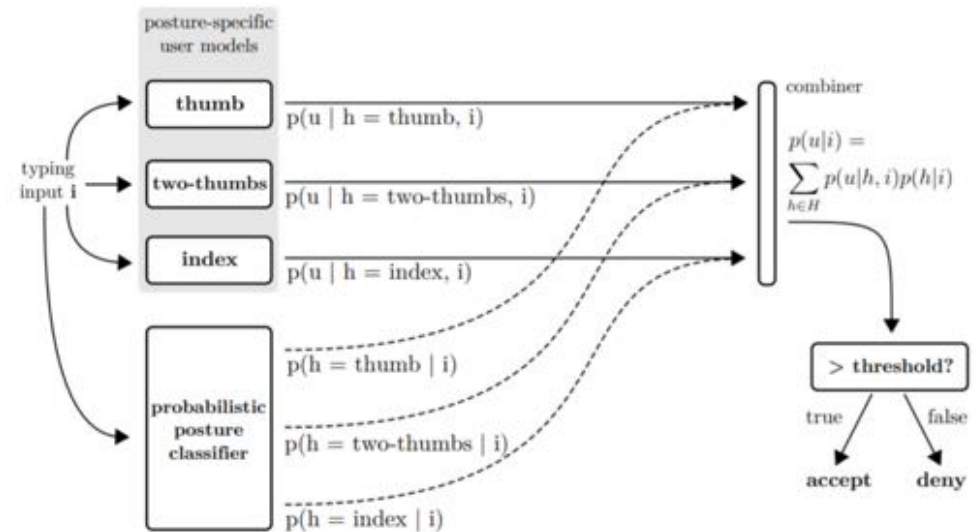
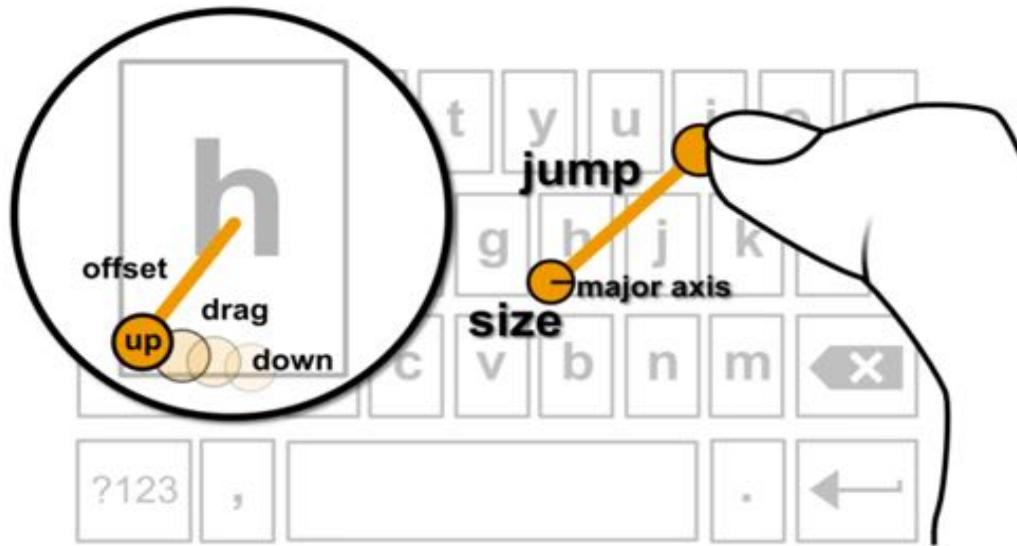
研究进展——多指滑动的身份认证

- 通过触摸屏传感器多个手指触控的坐标信息，计算手指间的相对距离，再基于距离特征数据构建认证分类器于身份认证。



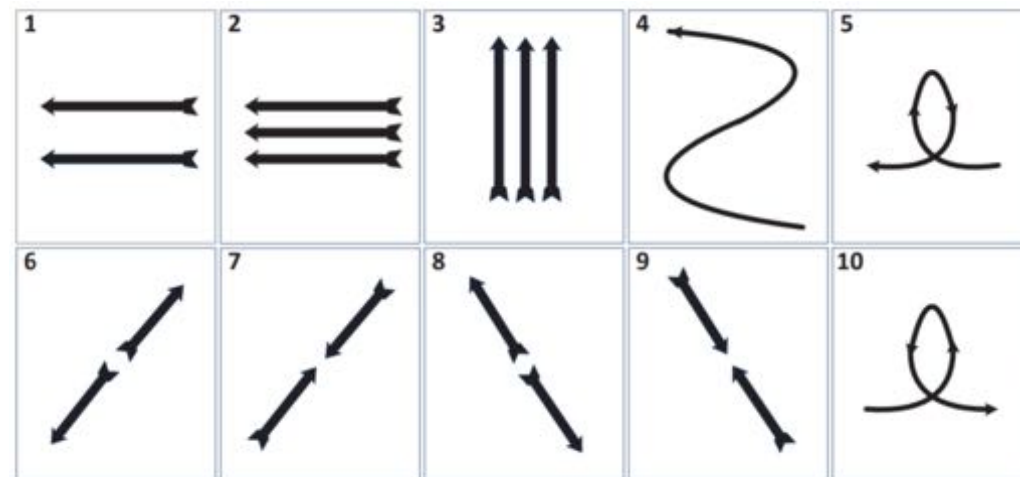
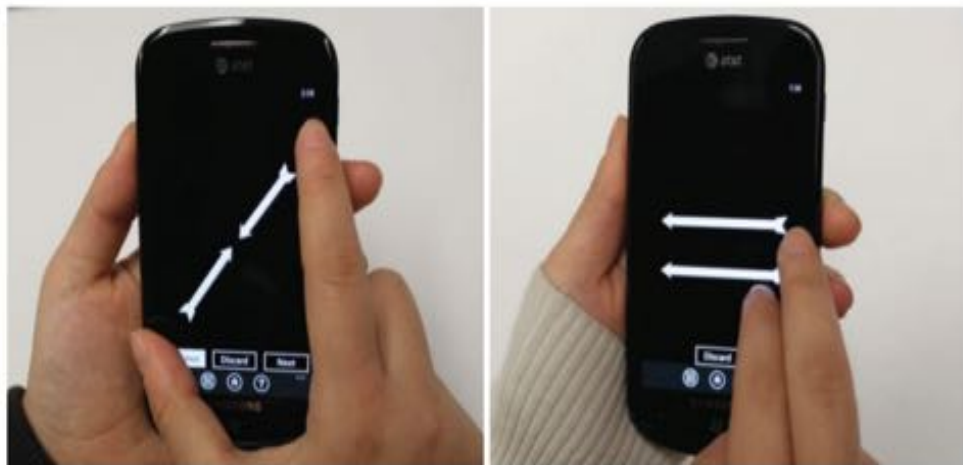
研究进展——击键行为的身份认证

- 通过触摸屏传感器感知用户敲击键盘的行为特征，如点击位置、拖动距离、按压面积等，再基于特征数据构建认证分类器于身份认证。



典型案例——触屏滑动手势的身份认证

- 如何基于智能手机的感知滑动手势的用户身份？



[1] Shahzad, M. , Liu, A. X. , & Samuel, A. . (2013). Secure unlocking of mobile touch screen devices by simple gestures - You can see it but you can not do it. Proceedings of the 19th annual international conference on Mobile computing & networking.

典型案例——触屏滑动手势的身份认证

- 数据采集与预处理：采集来自触摸屏传感器以及加速度计（辅助）的手势感知数据，并对坐标数据进行低通滤波

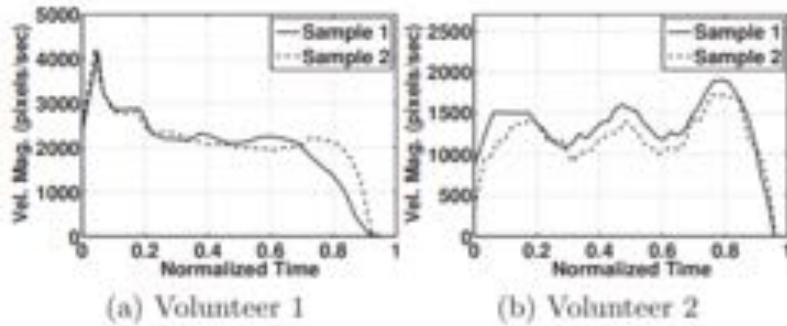


Figure 3: Velocity magnitudes of gesture 4

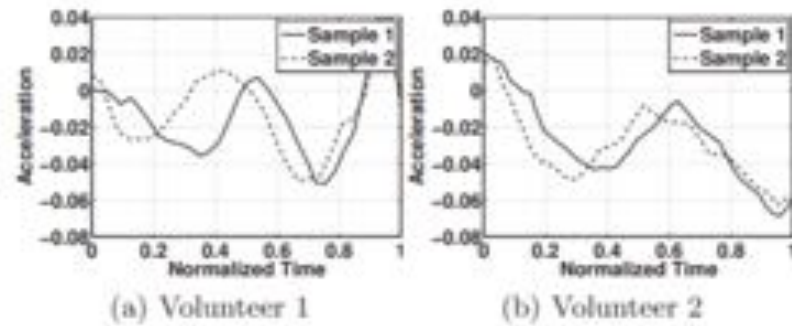
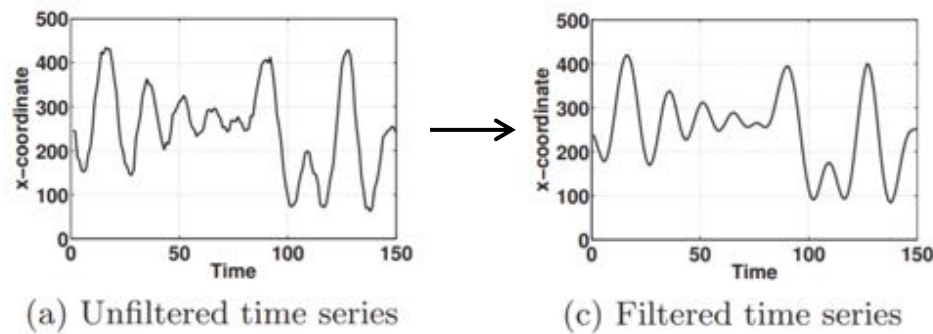


Figure 4: Device acceleration of gesture 4



[1] Shahzad, M. , Liu, A. X. , & Samuel, A. . (2013). Secure unlocking of mobile touch screen devices by simple gestures - You can see it but you can not do it. Proceedings of the 19th annual international conference on Mobile computing & networking.

典型案例——触屏滑动手势的身份认证

- 手势建模：基于预处理后的感知数据提取滑动速度、方向、时长、手指接触面积、手指间时间间隔（多指手势）、手势长度等特征

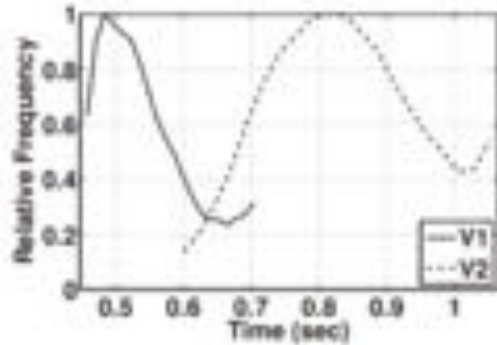


Figure 5: Distributions of stroke time

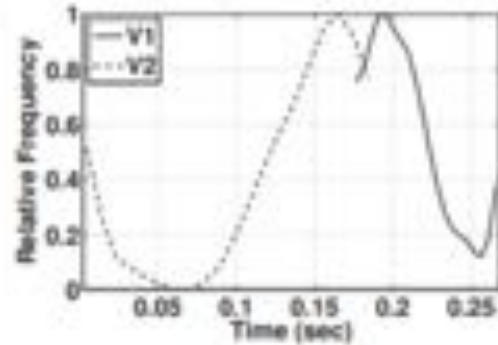


Figure 6: Distributions of inter-stroke time

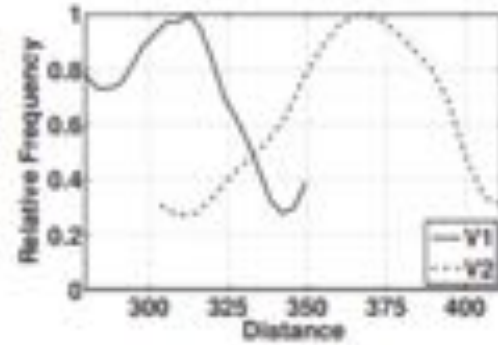


Figure 7: Distributions of stroke disp. mag.

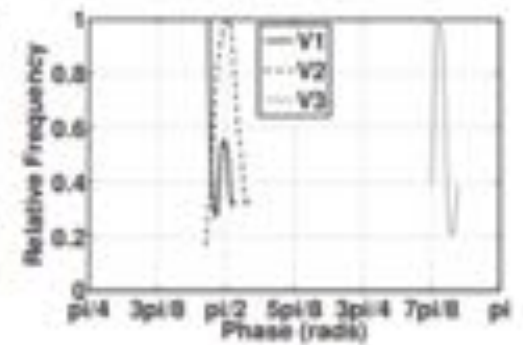
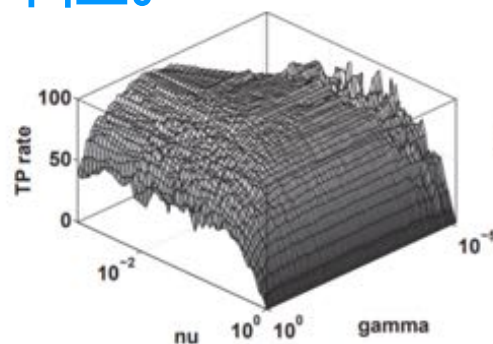


Figure 8: Distributions of stroke disp. direction

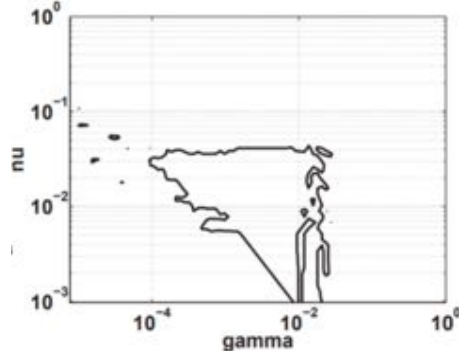
[1] Shahzad, M. , Liu, A. X. , & Samuel, A. . (2013). Secure unlocking of mobile touch screen devices by simple gestures - You can see it but you can not do it. Proceedings of the 19th annual international conference on Mobile computing & networking.

典型案例——触屏滑动手势的身份认证

- 身份认证：基于多个训练特征数据样本，构建单类SVM分类器区分合法非法用户；采用层次聚类区分不同姿势数据，以适应姿势变异性。



(a) TPR surface plot



(b) 95% TPR contour

Hand-holding posture



one-hand



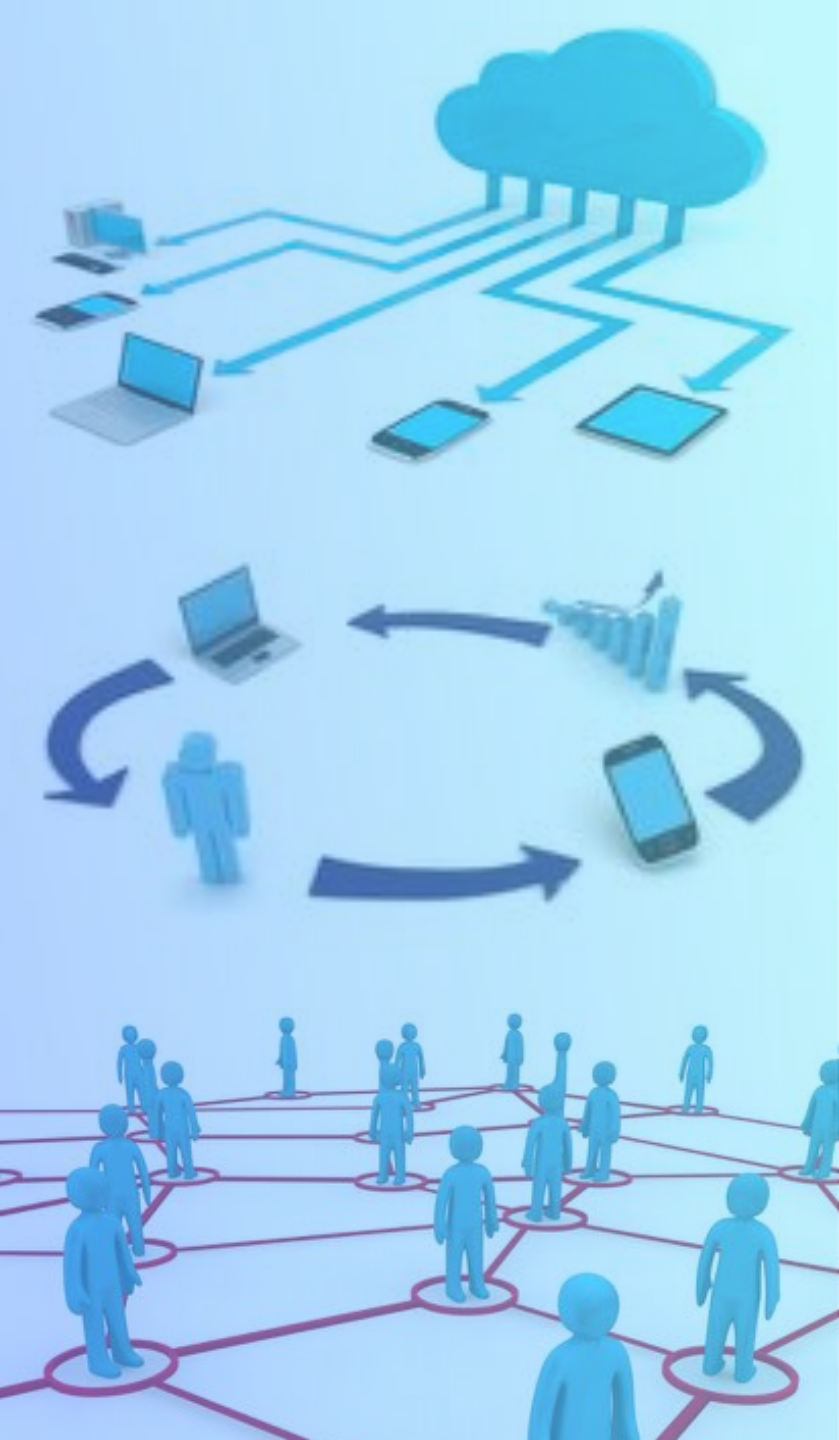
two-hand



(a) Two behaviors

(b) One behavior

[1] Shahzad, M. , Liu, A. X. , & Samuel, A. . (2013). Secure unlocking of mobile touch screen devices by simple gestures - You can see it but you can not do it. Proceedings of the 19th annual international conference on Mobile computing & networking.

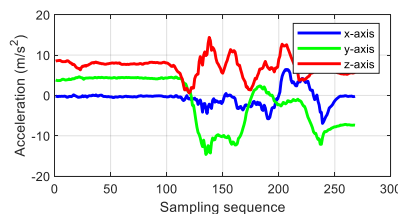
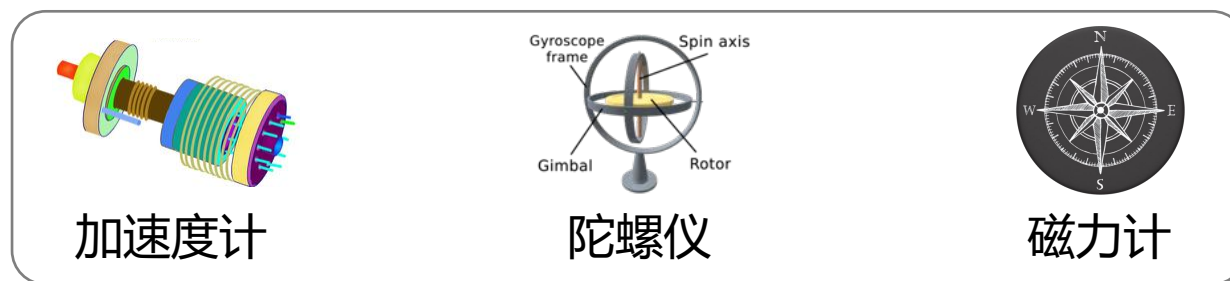
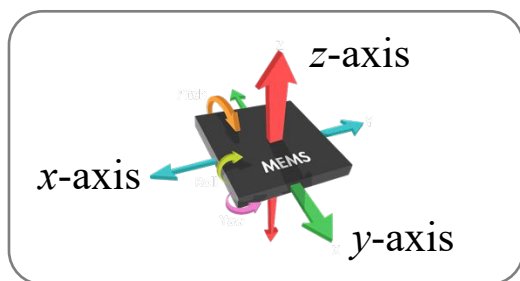


PART.4

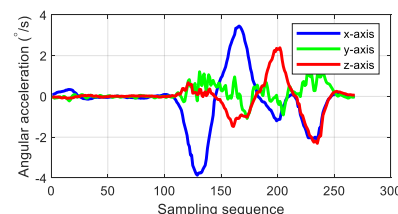
惯性感知技术

基本原理

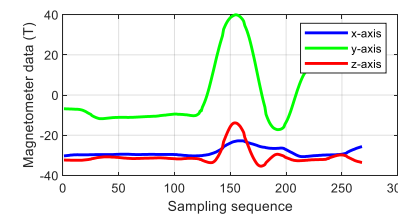
- 惯性传感器包括加速度计、陀螺仪、磁力计，用于获取目标对象在运动过程中对应的加速度、角速度、磁场强度数据，实现感知。



加速度



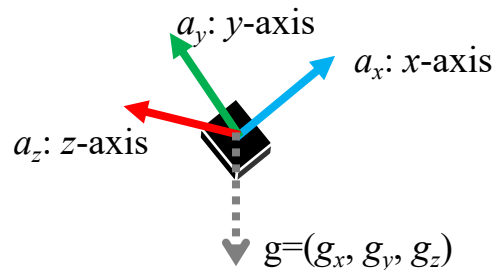
角速度



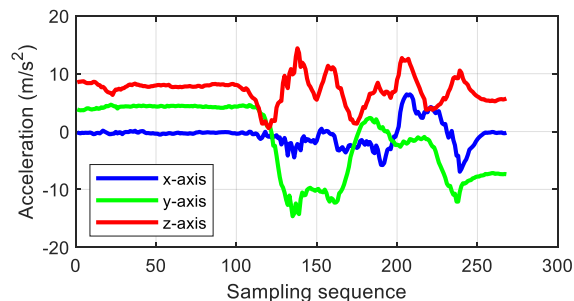
磁场强度

基本原理——典型的数据预处理方法

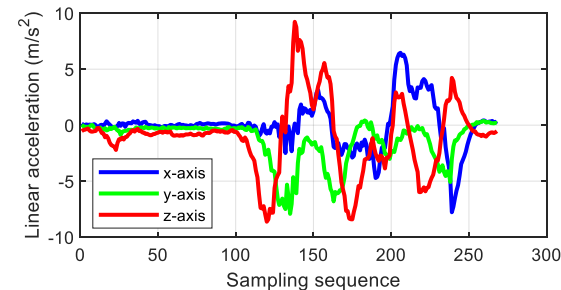
• 剔除重力



$$a - g = (a_x - g_x, a_y - g_y, a_z - g_z)$$

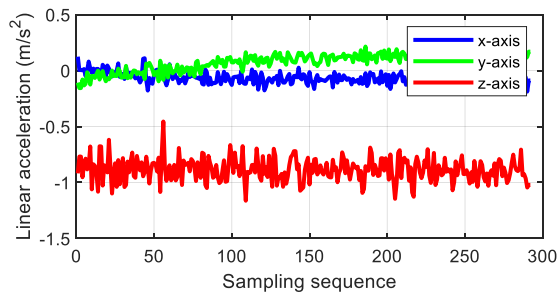


加速度



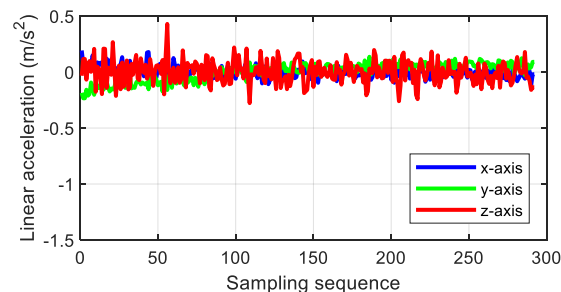
线性加速度

• 校正偏移



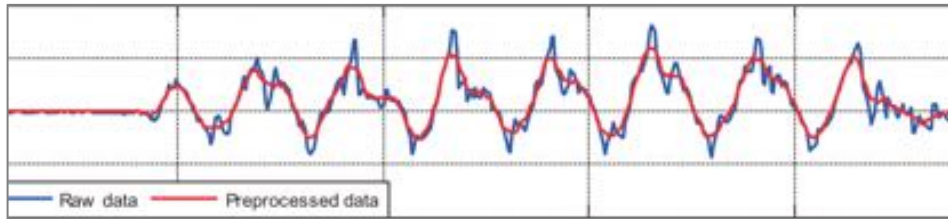
$$\delta \bar{a} = (\delta \bar{a}_x, \delta \bar{a}_y, \delta \bar{a}_z)$$

$$a - \delta \bar{a} = (a_x - \delta \bar{a}_x, a_y - \delta \bar{a}_y, a_z - \delta \bar{a}_z)$$



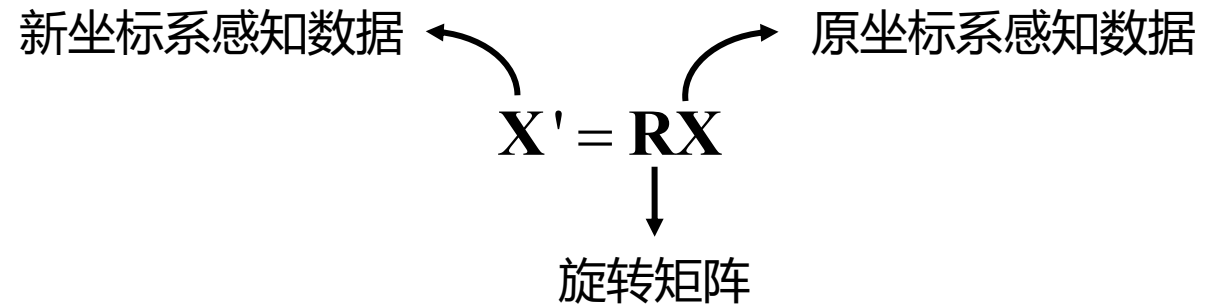
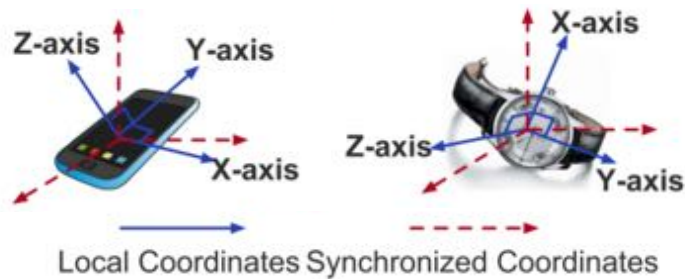
基本原理——典型的数据预处理方法

• 除噪



$$\hat{x}(t) = \frac{x(t) + x(t-1) + \dots + x(t-N+1)}{N}$$

• 坐标系转换

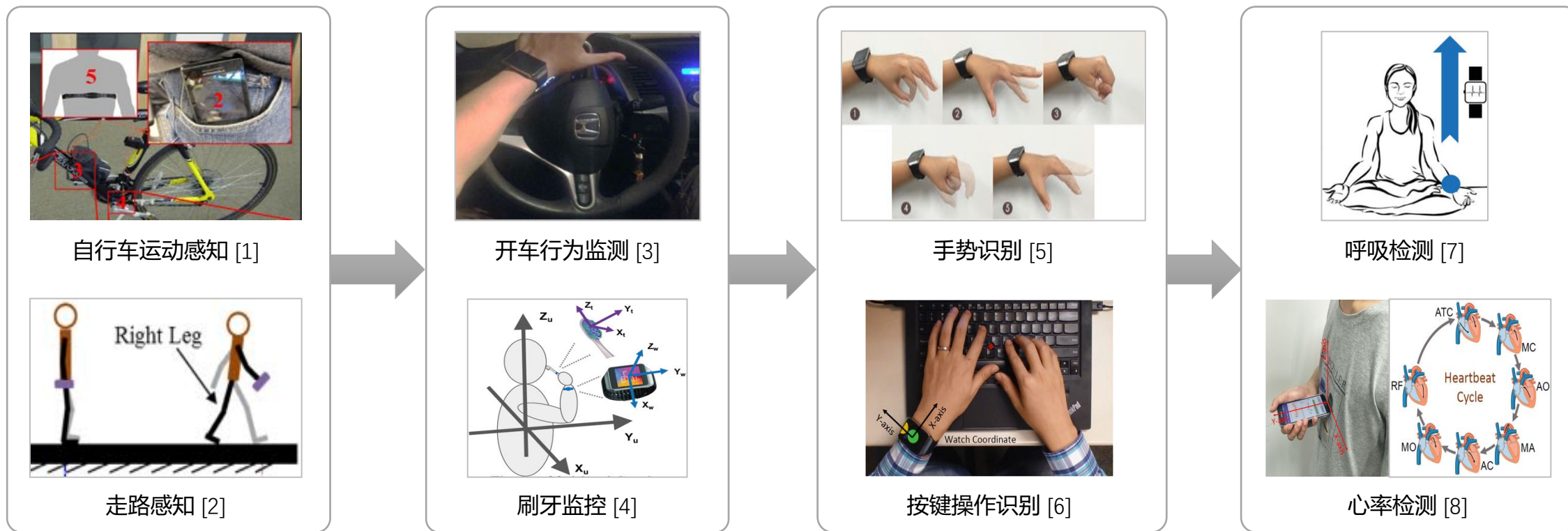


[1] Yafeng Yin, Lei Xie, Yuanyuan Fan, and Sanglu Lu. Tracking Human Motions in Photographing: A Context-Aware Energy-Saving Scheme for Smart Phones. ACM Transactions on Sensor Networks, vol. 13, no. 4, pp. 29, 2017.

[2] Lei Xie, Qingliang Cai, Alex X. Liu, Wei Wang, Yafeng Yin, and Sanglu Lu. Synchronize Inertial Readings from Multiple Mobile Devices in Spatial Dimension. IEEE/ACM Transactions on Networking, vol. 26, no. 5, pp. 2146-2159, 2018.

研究进展

从粗粒度感知到细粒度感知方向演进



[1] Zhan, A., Chang, M., Chen, Y., and Terzis, A, "Accurate caloric expenditure of bicyclists using cellphones," ACM SenSys, 2012.

[2] Huang, B., Qi, G., Yang, X., Zhao, L., and Zou, H., "Exploiting cyclic features of walking for pedestrian dead reckoning with unconstrained smartphones," ACM UbiComp, 2016.

[3] Karatas, C., Liu, L., Li, H., Liu, J., Wang, Y., Tan, S., Yang, J., Chen, Y., Gruteser, M., and Martin, R., "Leveraging wearables for steering and driver tracking," IEEE INFOCOM, 2016.

[4] Huang, H., and Lin, S., "Toothbrushing monitoring using wrist watch," ACM SenSys, 2016.

[5] Wen, H., Ramos Rojas, J., and Dey, A. K., "Serendipity: Finger gesture recognition using an off-the-shelf smartwatch," ACM CHI, 2016.

[6] Wang, H., Lai, T. T. T., and Roy Choudhury, R., "Mole: Motion leaks through smartwatch sensors," ACM MobiCom, 2015.

[7] Tian Hao, Chongguang Bi, Guoliang Xing, Roxane Chan, and Linlin Tu. 2017. Mindfulwatch: A smartwatch-based system for real-time respiration monitoring during meditation. ACM UbiComp, 2017.

[8] Wang, L., Huang, K., Sun, K., Wang, W., Tian, C., Xie, L., and Gu, Q., "Unlock with Your Heart: Heartbeat-based Authentication on Commercial Mobile Phones," ACM UbiComp, 2018.

研究进展——步态感知

- 通过拿在手中的智能手机内置惯性传感器感知走路行为，并通过坐标系转换、角度检测、零速校正、周期检测等计算走路步数、方向、步长。

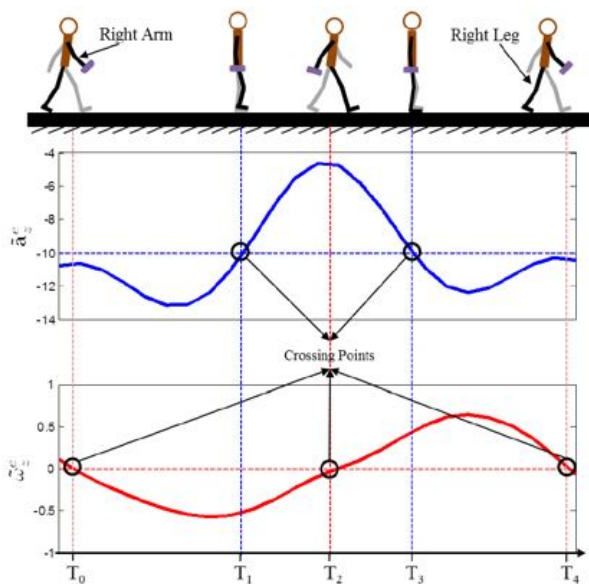


Figure 2. A gait cycle with a smartphone carried in hand. The blue and red dotted lines denote constant g_0 and 0 rad/s.

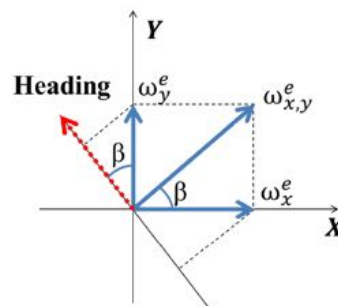
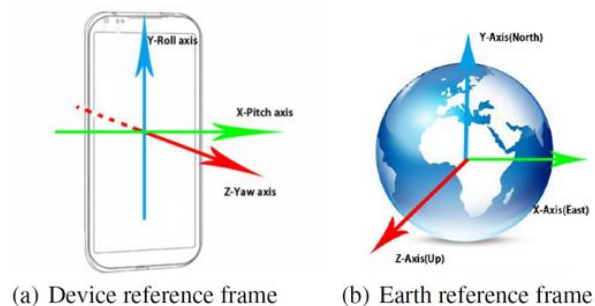


Figure 7. The relationship between the pedestrian heading and horizontal angular velocity.

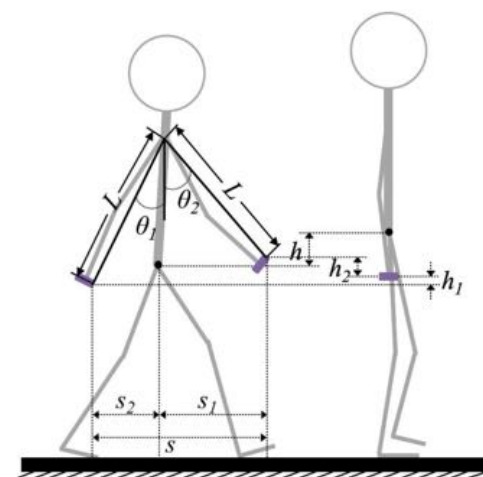
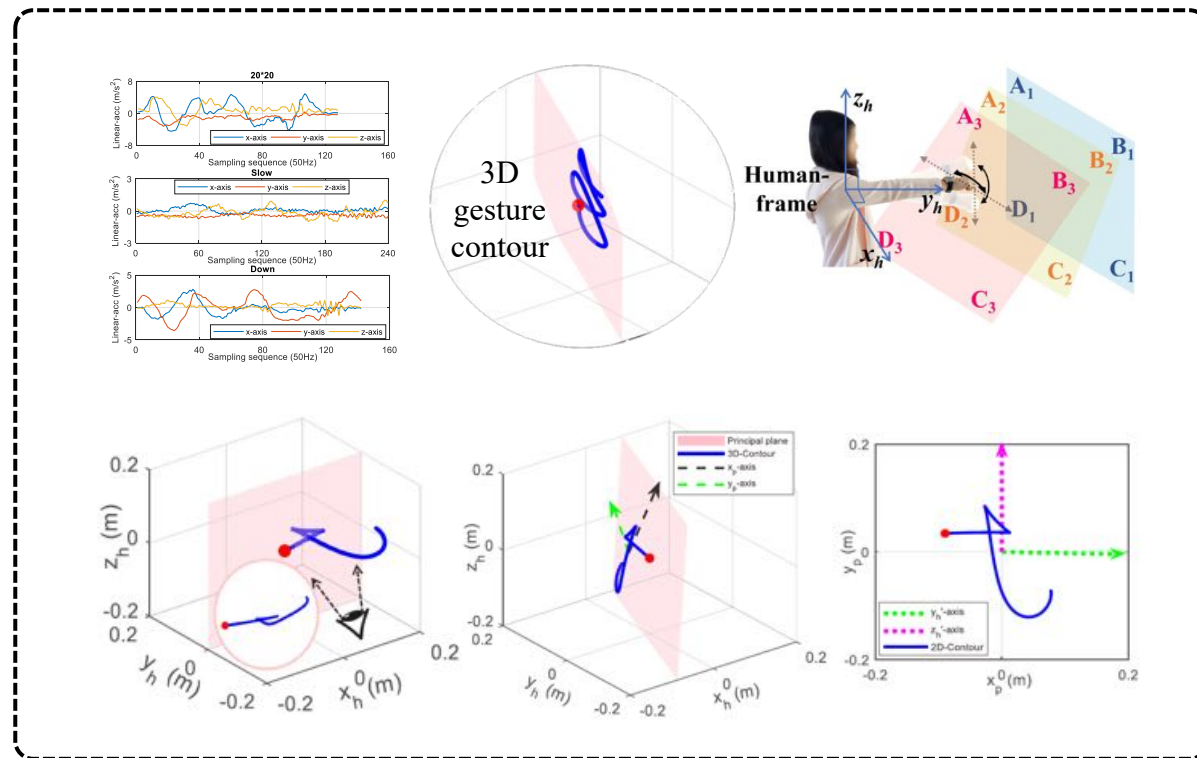
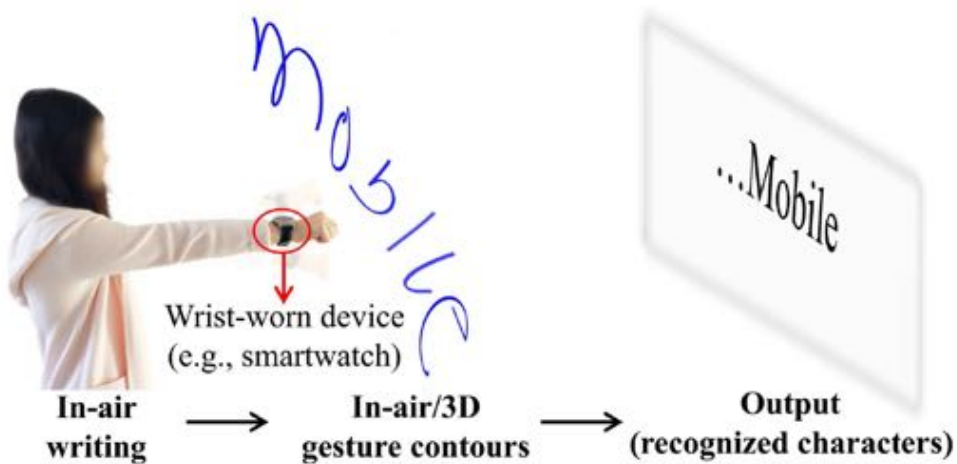


Figure 8. The step length estimation model with a smartphone held in the swinging hand.

[1] Huang, B., Qi, G., Yang, X., Zhao, L., and Zou, H., "Exploiting cyclic features of walking for pedestrian dead reckoning with unconstrained smartphones," ACM UbiComp, 2016.

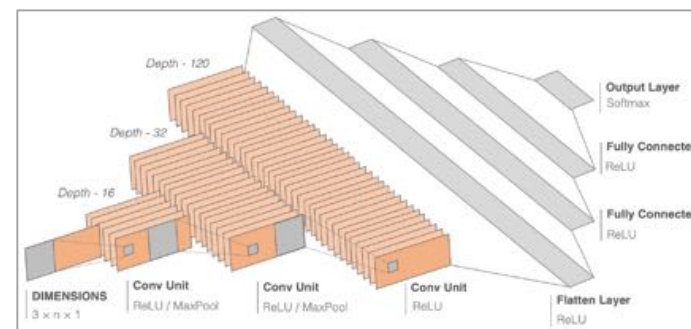
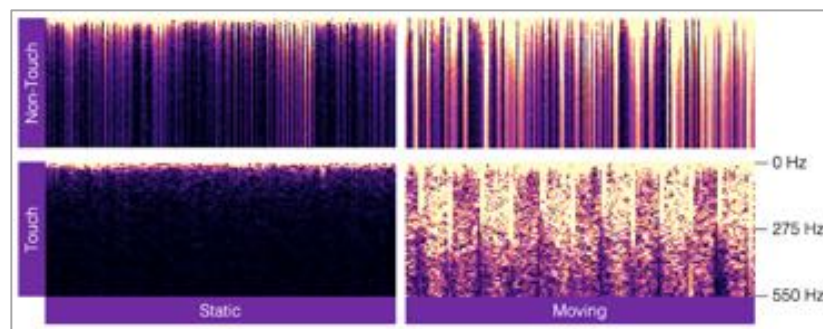
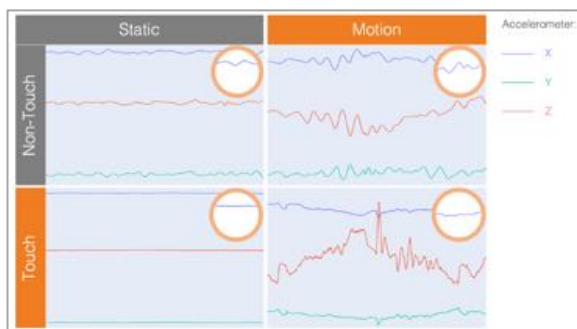
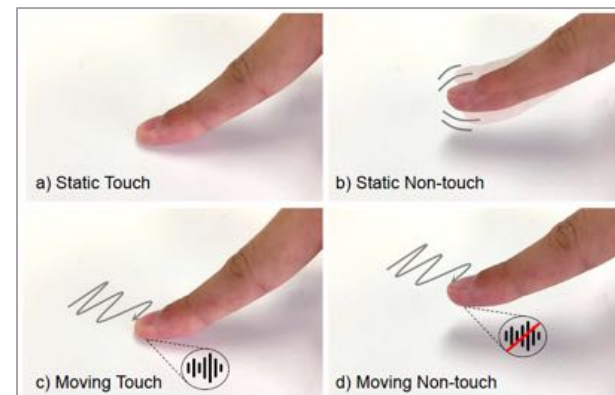
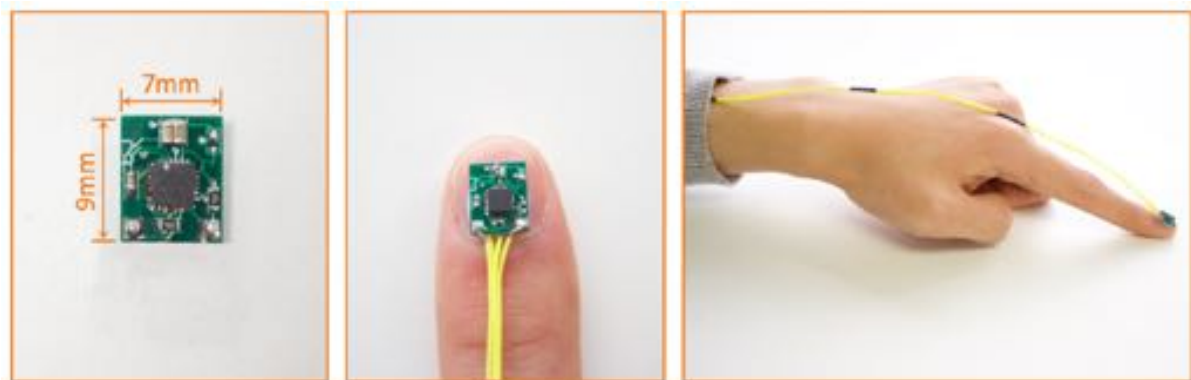
研究进展——手臂感知

- 通过手腕处的智能手表内置惯性传感器感知空中写字行为，提出**空间轮廓模型**将感知数据转化为3D轮廓，并采用**主平面检测**和**轮廓校正**获得2D字符轮廓，再采用分类器/神经网络进行识别。



研究进展——手势感知

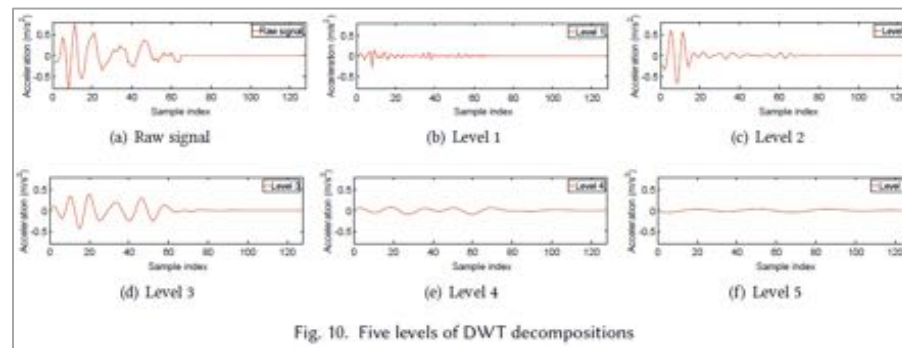
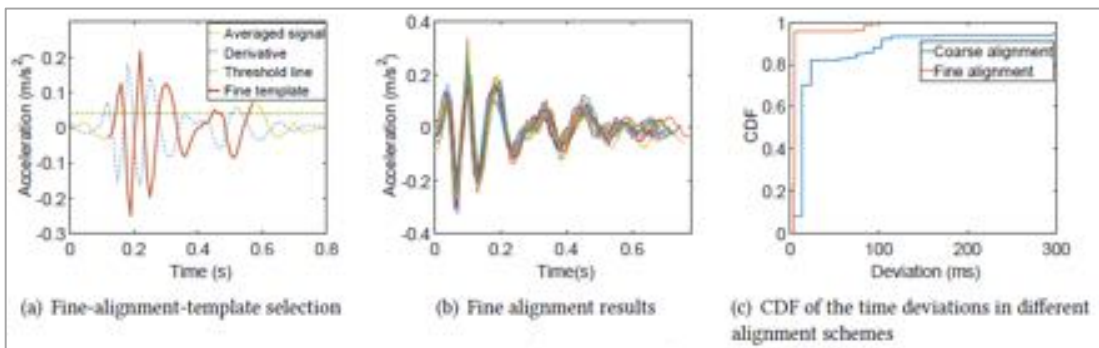
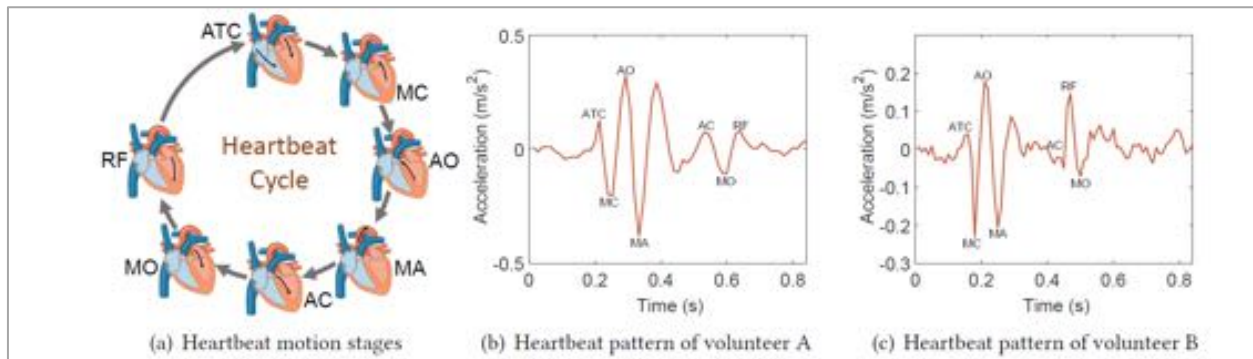
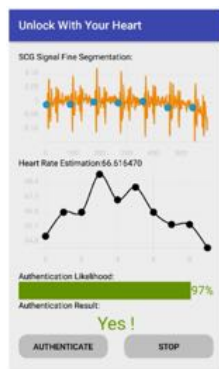
- 通过附着在指甲上的惯性传感器感知触摸和非触摸手势，将加速度的导数输入卷积神经网络实现触摸、非触摸手势识别。



[1] Yilei Shi, Haimo Zhang, Kaixing Zhao, Jiashuo Cao, Mengmeng Sun, Suranga Nanayakkara. Ready, Steady, Touch! — Sensing Physical Contact with a Finger-Mounted IMU. ACM UbiComp, 2021.

研究进展——心跳感知

- 通过放置在胸前的智能手机内置加速度计感知心跳，采用两阶段对齐和小波变换获取心跳特征输入到SVM分类器进行认证，并提出自适应模板选择机制提升其在不同状态下的稳定性。



[1] Wang, L., Huang, K., Sun, K., Wang, W., Tian, C., Xie, L., and Gu, Q., “Unlock with Your Heart: Heartbeat-based Authentication on Commercial Mobile Phones,” ACM UbiComp, 2018.

典型案例——基于惯性传感器的刷牙动作感知

- 如何基于手腕处的**智能手表**内置惯性传感器感知**16种刷牙行为**？
（其中，牙刷内置了磁铁，便于手表中的磁力计感知其运动）

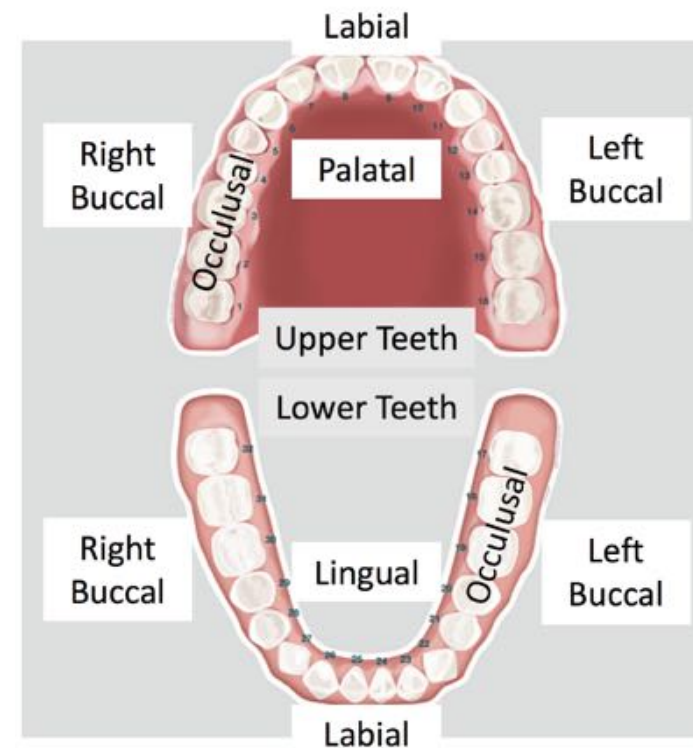
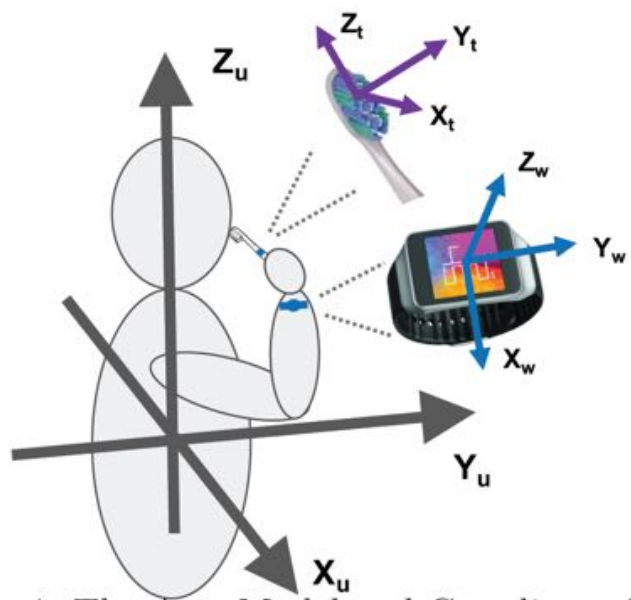


Figure 3: 16 Tooth Surfaces

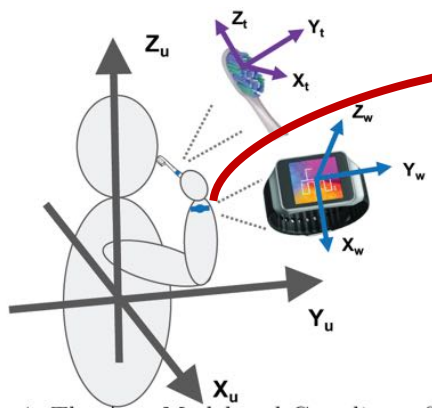
典型案例——基于惯性传感器的刷牙动作感知

- 感知牙刷方位和转动



Bass Technique

Incorrect Toothbrushing



$$\vec{B} = (B_x, B_y, B_z)$$

$$\vec{B} = \frac{\mu_0}{4\pi} \frac{3\vec{r}(\vec{r} \cdot \vec{m}) - \vec{m} |\vec{r}|^2}{|\vec{r}|^5}$$

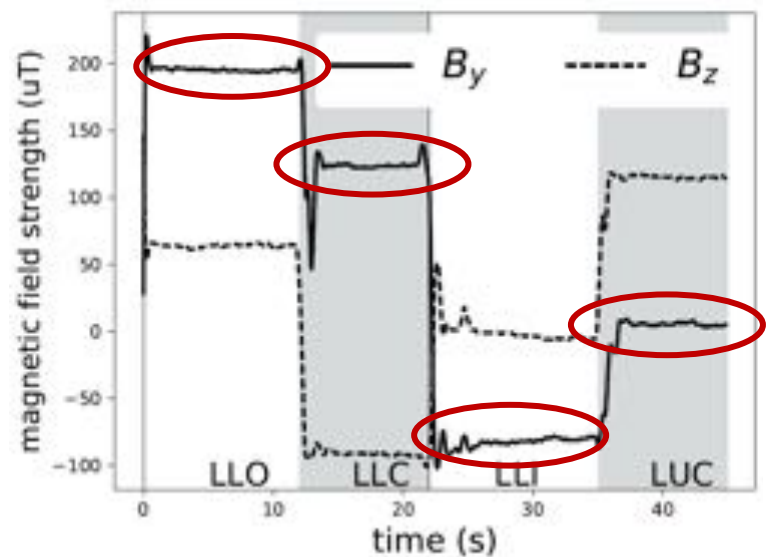
磁铁位置

磁铁方位

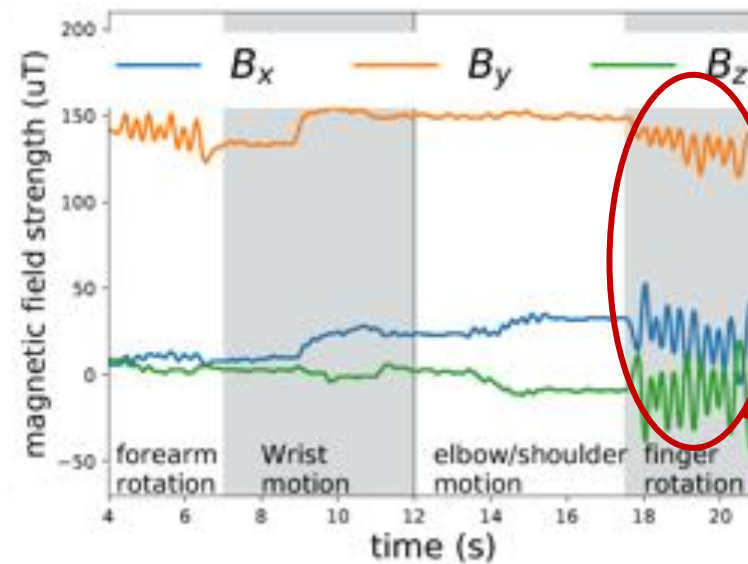


典型案例——基于惯性传感器的刷牙动作感知

- 感知牙刷方位和转动



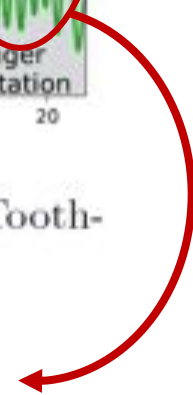
(a) Toothbrush Bristle Orientation



(b) Magnetic Sensing Data under Toothbrushing Gestures

磁力计读数与牙刷/磁铁方位（左下表面、左下咀嚼面、左下内表面、左上咀嚼面）的关系

牙刷/磁铁旋转



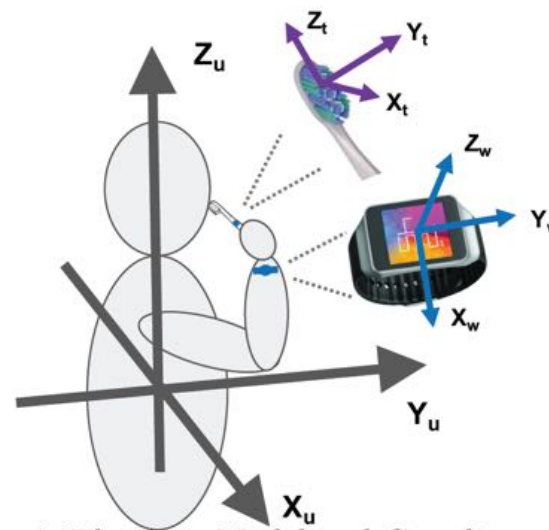
典型案例——基于惯性传感器的刷牙动作感知

- 坐标系转换：将传感器数据由设备坐标系转换到身体坐标系



Figure 9: Toothbrushing with Different Elbow Positions:(a)High Elbow Position, (b)Low Elbow Position

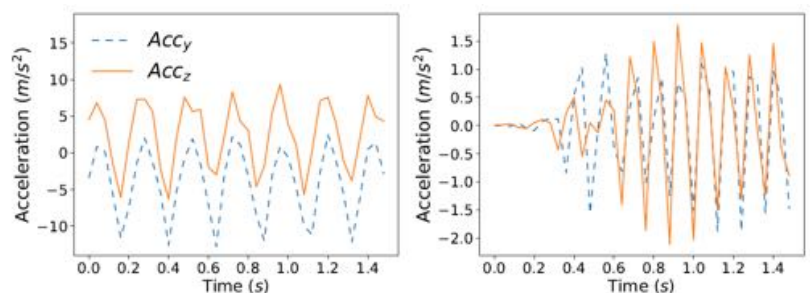
相同刷牙动作对应的手肘姿态差异



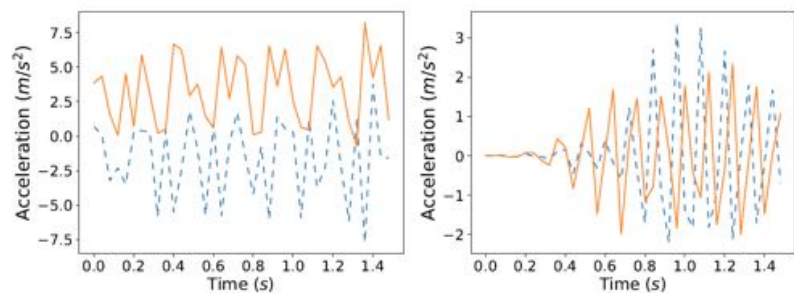
$$\begin{aligned} [0, 0, g] &= R * \vec{gravity} \\ [0, 1, 0] &= I * R * \vec{Y}_w \end{aligned}$$

典型案例——基于惯性传感器的刷牙动作感知

- 刷牙动作识别：提取功率谱密度、互相关系数、基于主成分的运动方向、平均值、方差、偏度等特征，采用单类SVM分类器区分正确、不正确刷牙行为，采用朴素贝叶斯分类器分类16种刷牙动作



(a) Acceleration Data of Elbow/Shoulder Motion (b) Band-pass Filtered Acceleration data of Elbow/Shoulder Motion



(c) Acceleration data of Wrist Motion (d) Band-pass Filtered Acceleration data of Wrist Motion

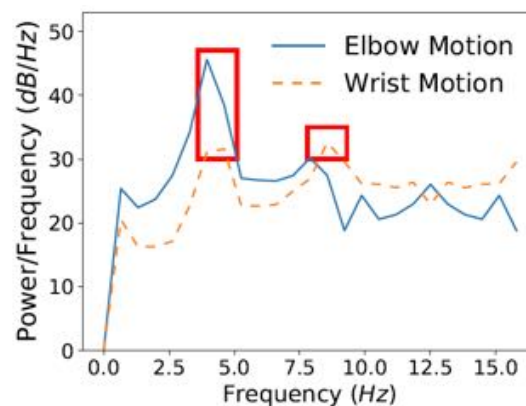


Figure 7: Power Spectrum of Elbow and Wrist Motion Acceleration Data

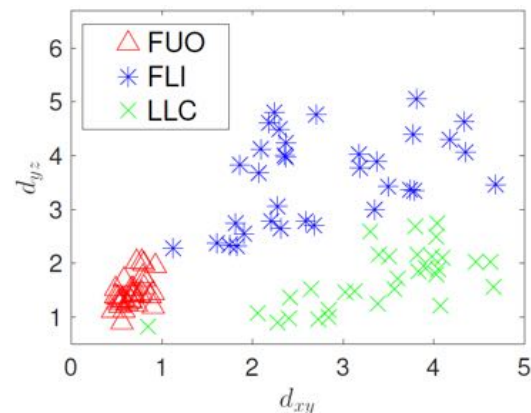
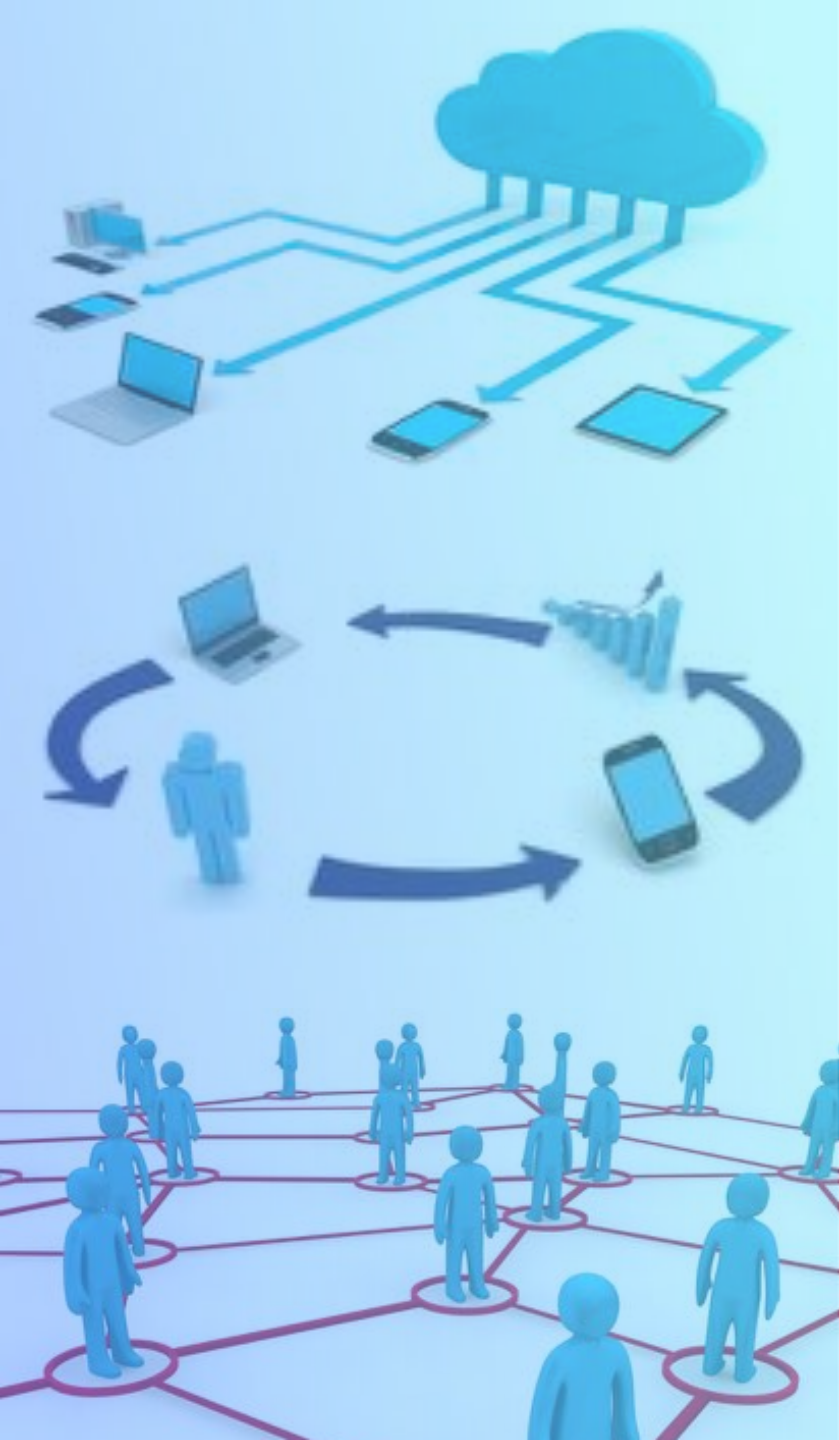


Figure 8: PCA Direction Feature



PART.5

其他感知技术

二维码感知技术

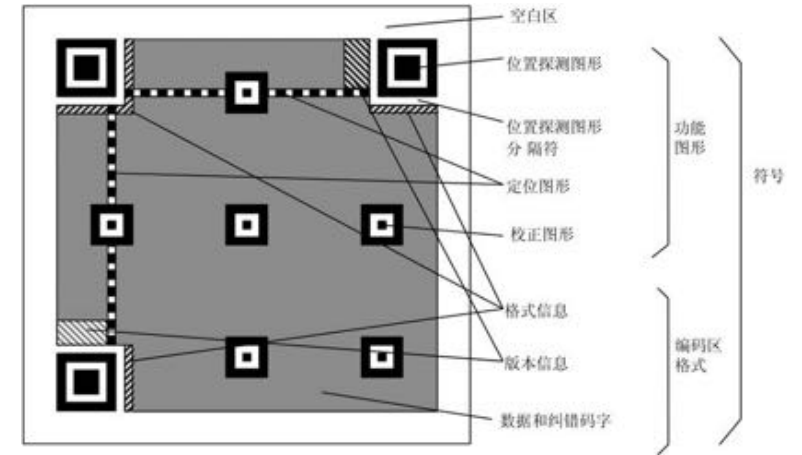
- 二维码通过按照特定的规律分布在二维平面上的，黑白相间的图形记录信息。



堆叠式二维码

- 二维码分为堆叠式和矩阵式

- 堆叠式/行排式：由多行一维条码堆叠而成（Code 16K、Code 49、PDF417等）
- 矩阵式：以矩阵的形式组成，用点表示二进制1，用空白表示二进制0（QR CODE自1994年问世，一直沿用至今）



矩阵式二维码(QR Code)结构

二维码感知技术——基本原理

• 图像预处理

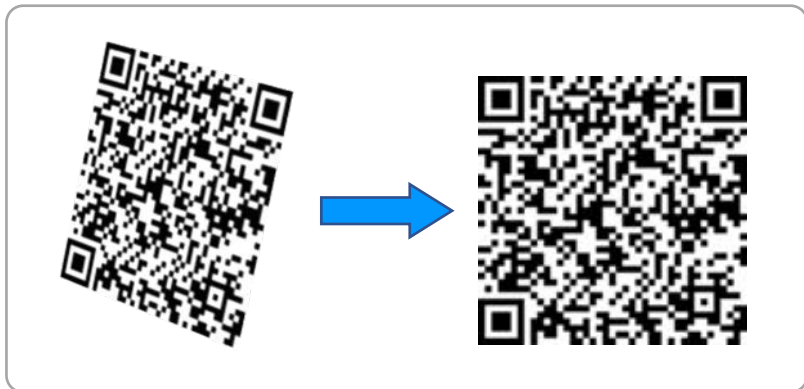


• 定位位置探测图形：通过位置探测图形1:1:3:1:1的特征查找，水平和垂直方向扫描特征



二维码感知技术——基本原理

- 透视变换

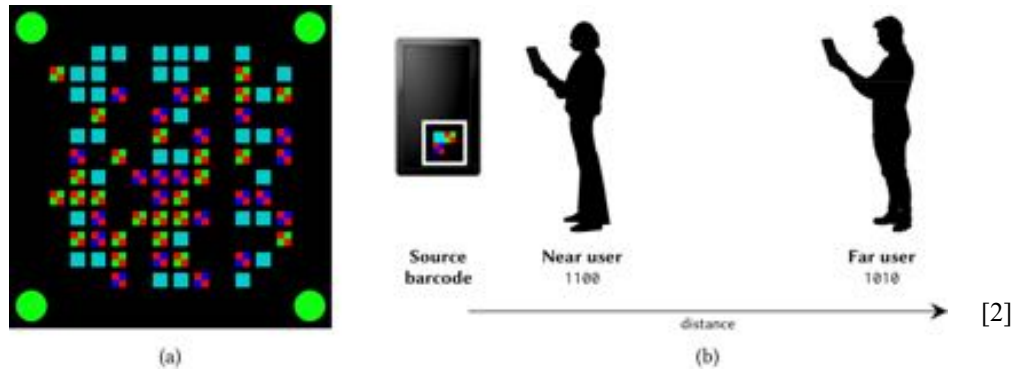
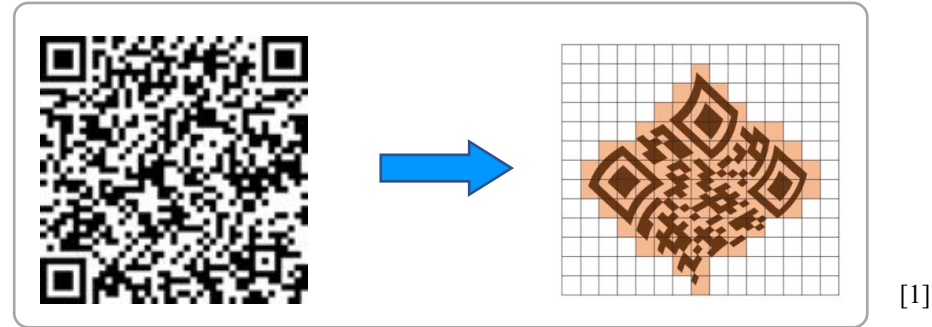


$$\begin{pmatrix} X \\ y \\ Z \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} u \\ v \\ 1 \end{pmatrix}$$

- 译码和校验：将数据区转为0和1的比特流，并用Reed-Solomon纠错算法对比特流校验和纠错。

二维码感知技术——研究进展

- 从简单二维码感知到鲁棒的，场景相关的二维码感知

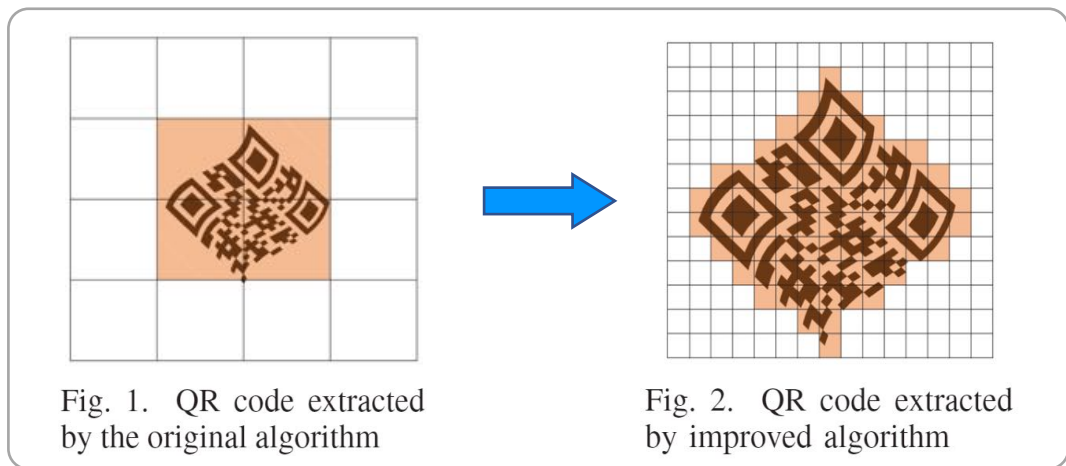


[1] Jiamei Lv, Yuxuan Zhang, Wei Dong, Yi Gao, Chun Chen, A General Approach to Robust QR Codes Decoding. 2020 IEEE/ACM IWQoS.

[2] Palomäki, Roope, Maria L. Montoya Freire, and Mario Di Francesco, Distance-Dependent Barcodes for Context-Aware Mobile Applications, MobileHCI '20.

二维码感知技术——研究进展：鲁棒的二维码感知

- 改进现有的QR码检测算法，根据白黑交错排列的结构特征提出了**畸变校正机制**，使用滑动窗口来匹配QR码中的每个模块。并结合多个QR码**重构完整目标**，解决部分不可见问题。

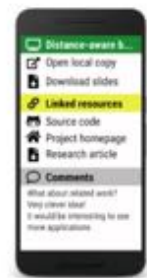
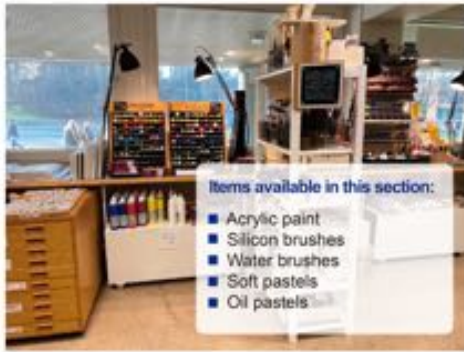


用滑动窗口匹配QR Code各个模块

[1]

二维码感知技术——研究进展：距离相关的二维码感知

- 采用**颜色混合**作为实现距离依赖性的关键技术，并设计了一种有效的编码方案以区分近距离用户和远距离用户。

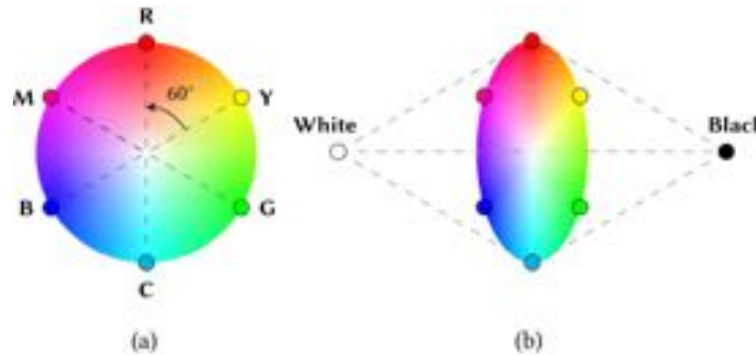


(a)

(b)

(c)

Figure 2: (a) Distance-dependent barcodes for casual interactions with public displays; user interface for (b) presenter and (c) audience.



(a)

(b)

Near data	Far data					
	0	1				
0	Black	<table border="1"> <tr><td>R</td><td>B</td></tr> <tr><td>B</td><td>R</td></tr> </table>	R	B	B	R
R	B					
B	R					
1	<table border="1"> <tr><td>R</td><td>G</td></tr> <tr><td>G</td><td>R</td></tr> </table>	R	G	G	R	Cyan
R	G					
G	R					

(c)

Near data	Far data	
	0	1
0	Black	Magenta
1	Yellow	Cyan

(d)

[1] Palomäki, Roope, Maria L. Montoya Freire, and Mario Di Francesco, Distance-Dependent Barcodes for Context-Aware Mobile Applications, MobileHCI '20.

二维码感知技术——典型应用

- 二维码移动支付：商家将购物支付信息编码后以二维码的方式呈现，顾客通过移动设备扫描并解析二维码，进行添加购物车、下单、支付等操作。



UWB感知技术

- **UWB**：超宽带无线通信技术(Ultra Wideband)。
- **UWB**收发具有纳秒或微秒级以下的极窄脉冲来实现无线传输、**空间感知**、**行为感知**。
- **UWB感知定位算法**：TOF、TDOA、PDOA。



UWB芯片



空间感知

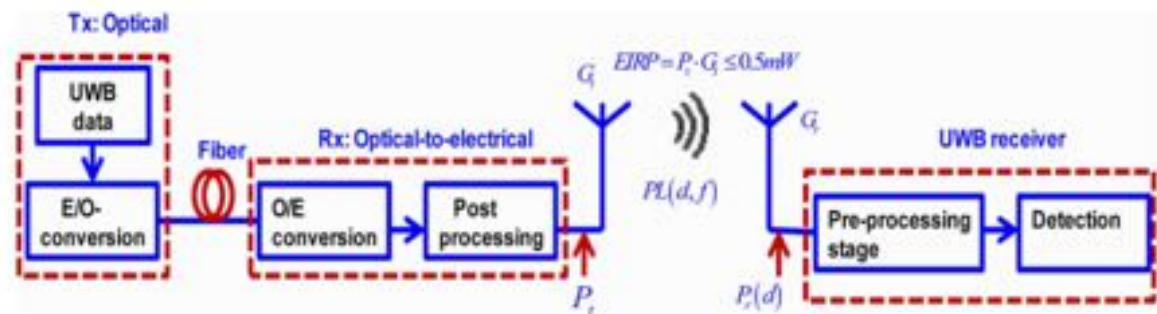
基本原理

- UWB技术基于IR-UWB信号脉冲
- IR-UWB使用短的能量脉冲序列，将信号发射。
- IR-UWB信号vs连续波信号：

(1) 不需要产生连续的高频载波，仅需要产生一个时间短至nS级以下的脉冲。

(2) 连续波信号将能量集中于一个窄频率内，而UWB信号带宽很大。

(3) 相对于连续波信号定位精度高。



IR-UWB System

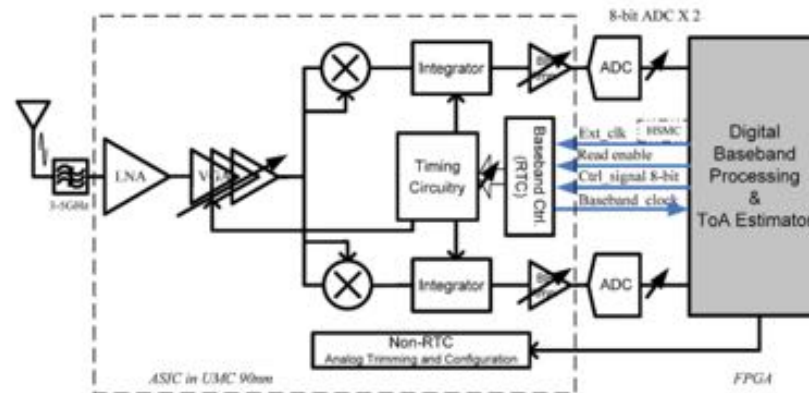


Fig. 5. Proposed flexible energy detection IR-UWB receiver architecture.

[1] Abraha S T, Okonkwo C, Gamage P A, et al. Routing of power efficient IR-UWB wireless and wired services for in-building network applications[J]. Journal of Lightwave Technology, 2012, 30(11): 1651-1663.

[2] Zou Z, Mendoza D S, Wang P, et al. A low-power and flexible energy detection IR-UWB receiver for RFID and wireless sensor networks[J]. IEEE Transactions on Circuits and Systems I: Regular Papers, 2011, 58(7): 1470-1482.

空间定位基本原理TDOA

利用UWB技术测得定位标签相对于两个不同定位基站之间无线电信号传播的时间差：

$$\begin{cases} d_{i,12} = r_{i,1} - r_{i,2} \\ d_{i,23} = r_{i,2} - r_{i,3} \\ d_{i,34} = r_{i,3} - r_{i,4} \\ d_{i,14} = r_{i,1} - r_{i,4} \end{cases}$$

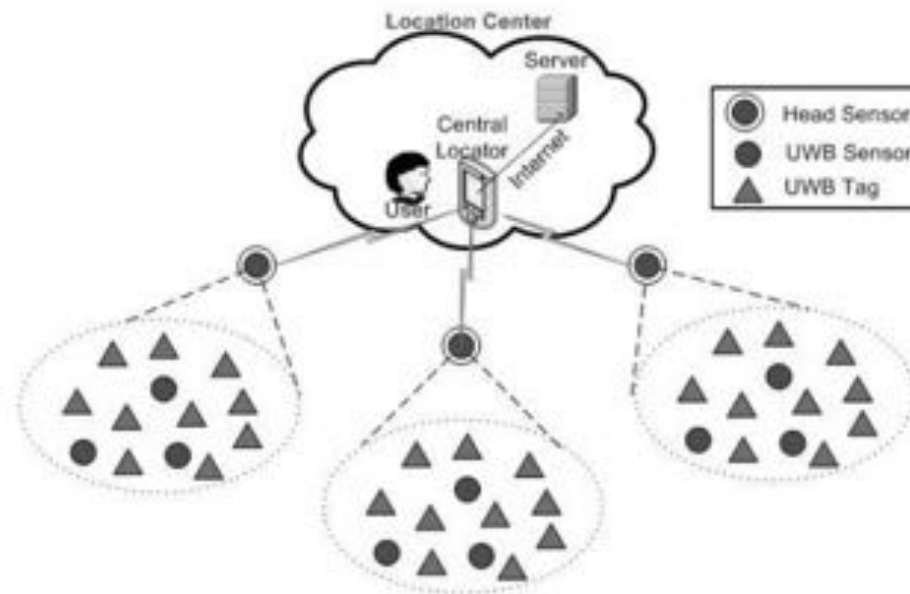


Figure 1. Location network layout

研究进展——多人检测

- IR-UWB雷达获取信号，通过反卷积技术评估信道脉冲响应，滤去杂波，寻找有效峰值。将功率信号划分多个相干簇，等价于目标数量。

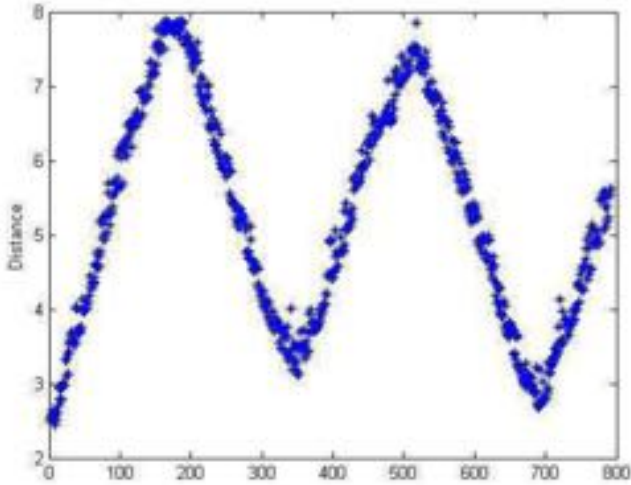


Fig 2. The tracing results for the case of one person

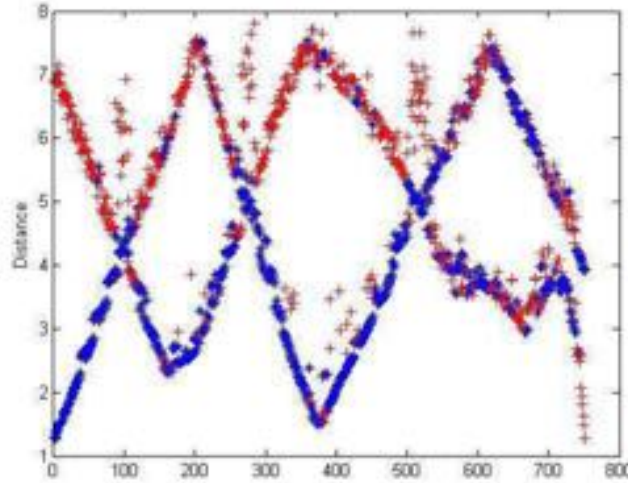


Fig 3. The tracing results for the case of two persons

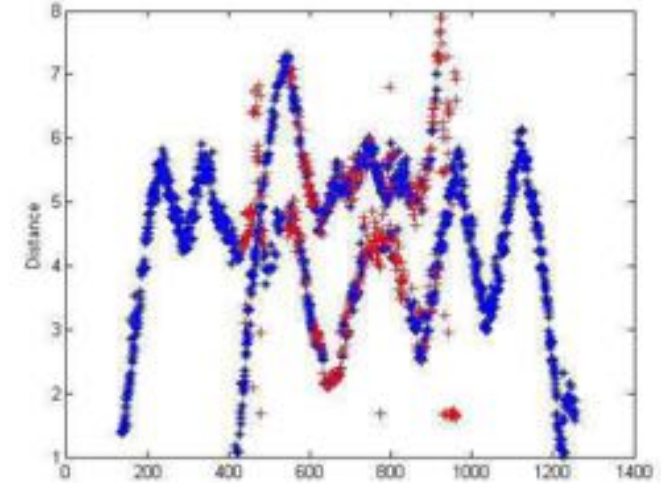


Fig 4. The tracing results for the case of changing the number of humans to be one-two-one

研究进展——手势识别

- 利用IR-UWB雷达获取获取手势的反射信号，将手势持续时间分成多个部分，神经网络训练以进行手指计数分类。

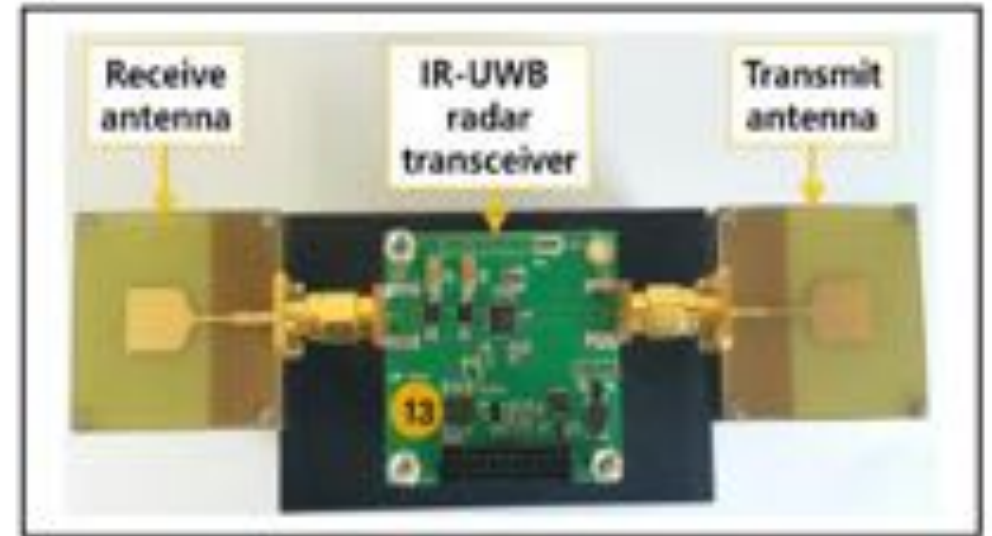
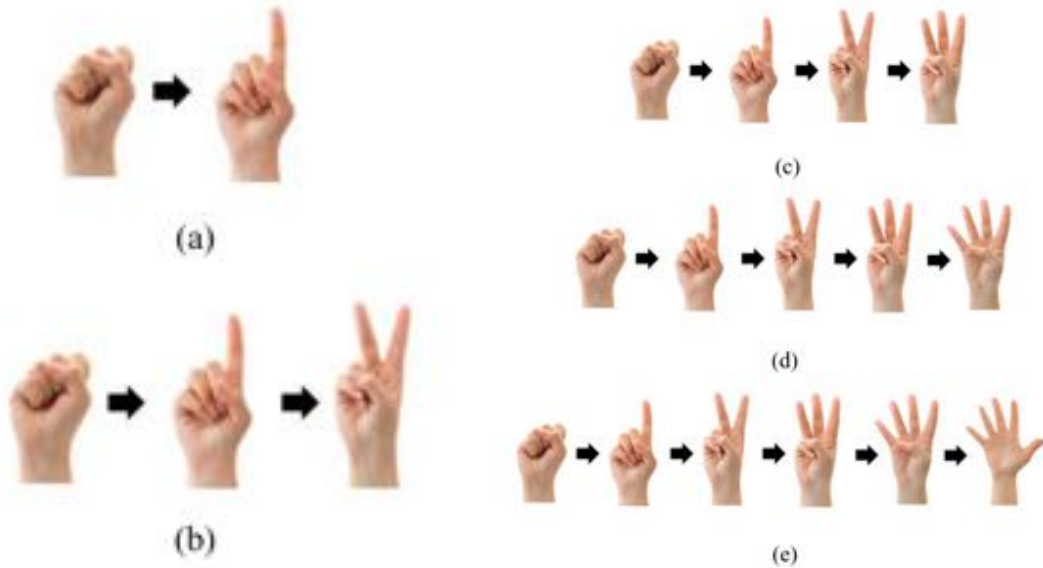


Fig. 2. IR-UWB radar sensor module

研究进展——生命体征检测

- 利用IR-UWB雷达获取从人体反射的呼吸谐波信号。利用自相关判断人体运动状态，判断为静止状态时，使用傅里叶变换等方式将心率信号从呼吸谐波中分离出来，估计心率。

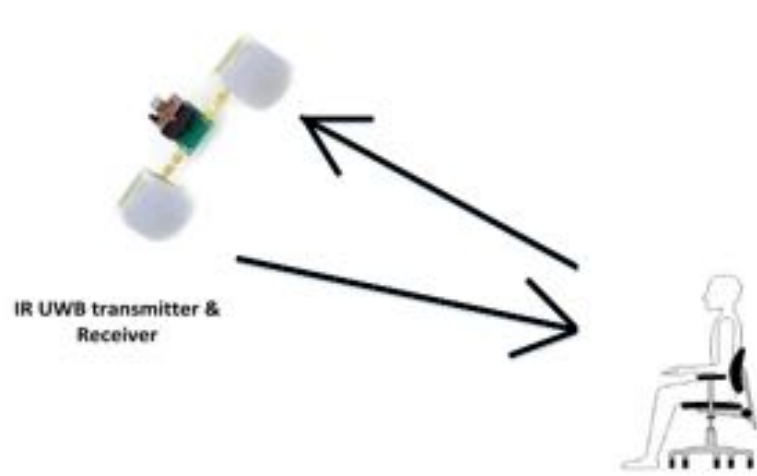


Figure 1. Experimental setup.

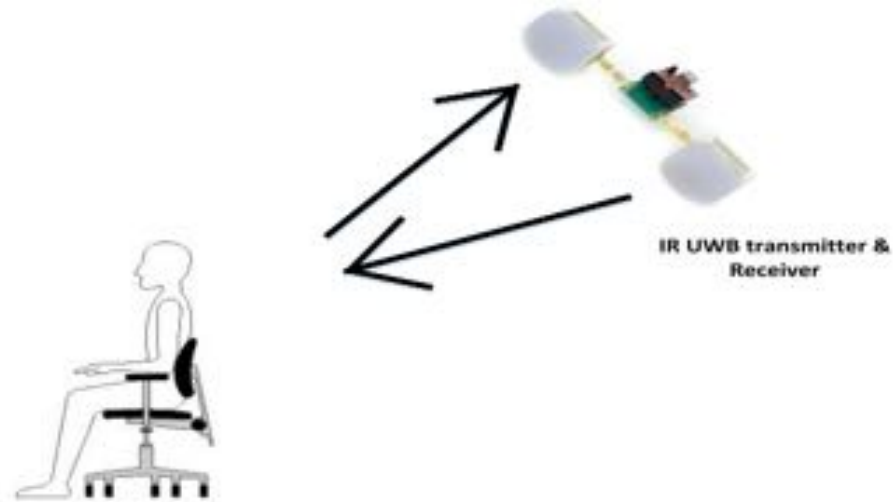
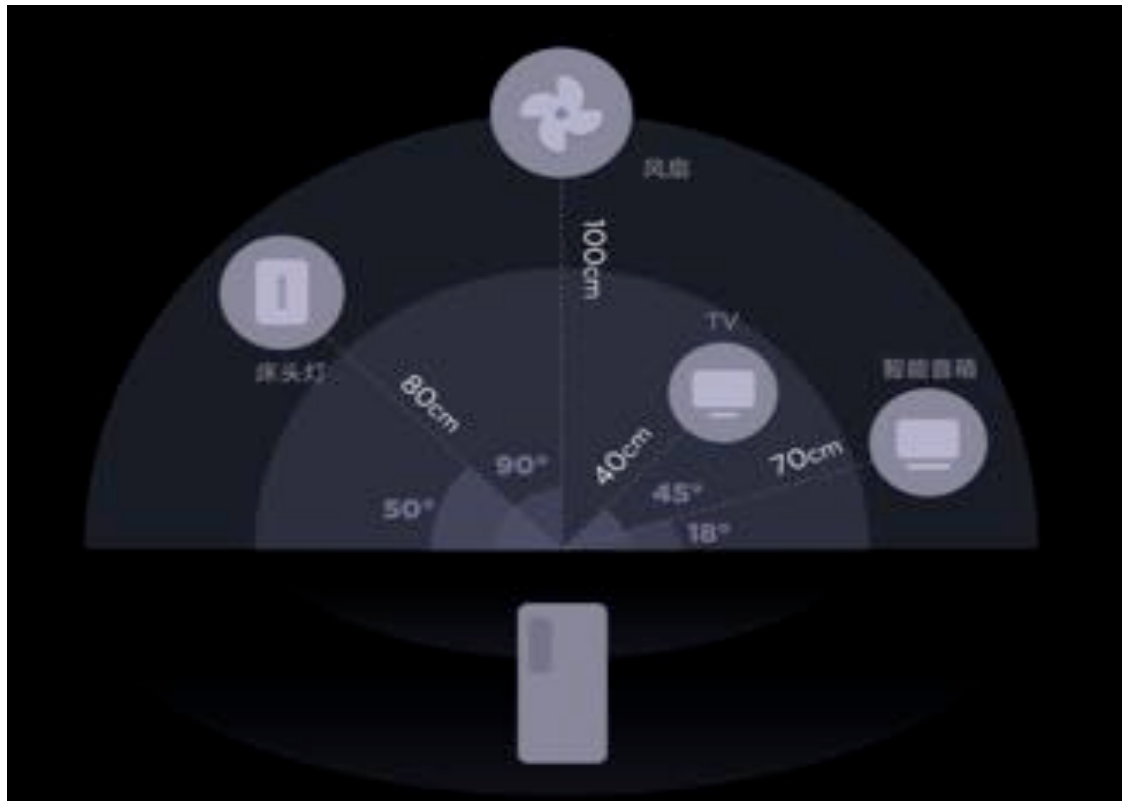


Figure 12. Experimental setup when the radar is pointed at the back of the subject.

典型案例

- 指向交互：手机的UWB芯片发射脉冲信号，接受智能家具内置天线阵列的反射信号。使用TDOA等算法感知设备之间的距离和角度，对指定距离和角度的设别发射控制命令，实现用户与设备的指向性交互。





本章完