

1. PPG (指尖摄像头) -> Transformer(Audio) + Feature Selection(Manual) -> 血糖(BG)和血压(BP), 心率(HR)回归
2. 生成(Image2styleGAN)插帧的图像(当作帧缺失来降噪) + 置信度低的帧丢弃(ICML) 或 (VideoMoCo)。Loss 监督用 (特征图蒸馏)
3. 因果处理+证明 (插入到 U 型另一边)
4. 人工特征用频率插入到 Tokens, 或者参看特征融合(Transformer)
5. Baseline 用 ParNet (transformer 改, 卷积 weight 改 Pruning Self-attentions into Convolutional Layers, Self-attention-ConvLSTM 插入), 做多阶段不同 token 长度(Not all 16*16)
6. 线性分析得到心率, 血压, 血糖的关系

■ 自监督学习任务和标签自动生成——解耦+验算

目标任务	Pretext task	自监督学习目标函数
面部动作单元 (AU)检测	人脸视频中面部运动由AU和姿态变化叠加而来, 解耦二者, 只取AU部分即可	$F(TAU(x_i) + T_{pose}(x_i)) = F(x_{i+k})$ 1. 正确的解耦要求各自的重构误差小; 2. 正确的解耦再合并重构误差小;
基于面部视频的心率估计	将面部视频解耦为生理信号 (rPPG)部分与噪声(非生理信号)部分, 生理信号部分用于估计心率	两段视频各自解耦: $x_1 \rightarrow p_1 + n_1; x_2 \rightarrow p_2 + n_2$ 1. 各自重构误差小; 2. 交换 p_1 和 p_2 , 各自重构输入再解耦, 解耦后 p 误差和 n 误差均要小;

The screenshot shows a video player with a Bilibili interface. The video title is "Previous Theory on Encoding GANs (BiGAN)". The content is a slide titled "Theory of BiGAN" which includes a theorem by Donahue et al. (2016). The theorem states that if the encoder e and generator g are optimal by adversarial training, then $e = g^{-1}$ a.e. on the data manifold, and $g = e^{-1}$ a.e. on the latent manifold. The slide also includes the formula for the loss function $V(E_\theta, G_\phi, D_\psi)$ and the statement "Encoding shouldn't be harder than generating!". The video player shows the user is Ruili Feng (USTC) and the video is from the "Uncertainty Principles of Encoding GANs" series, dated October 31, 2021.

Training Gan 的方式去 training encoder, 会收敛到 generator 的逆, 也就是原始数据

Assumptions

- Neural networks are all locally Lipschitz;
- Distributions are all absolutely continuous;
- Data domain is a manifold;
- $\dim(\mathcal{Z}) \neq \dim(\mathcal{X})$.

The first three are almost the minimum requests for serious theoretical analysis. The last one almost always holds in practice.

Ruli Feng (USTC) Uncertainty Principles of Encoding GANs October 31, 2021 30 / 56

证明所用的基本定理

因果作用

- 个体因果作用:

$$ICE(i) = Y_1(i) - Y_0(i).$$

Heraclitus (东罗马皇帝): 你不可能两次踏入相同的河.
'You can't step into the same river twice.'

- 平均因果作用(ACE):

$$ACE(T \rightarrow Y) = E(Y_1 - Y_0) = E(Y_1) - E(Y_0).$$

(健康人-不健康) 插入因果