Google Research x SNU

# Explore CSR Workshops

## Sleep AI : Noncontact to Estimate Sleep Apnea


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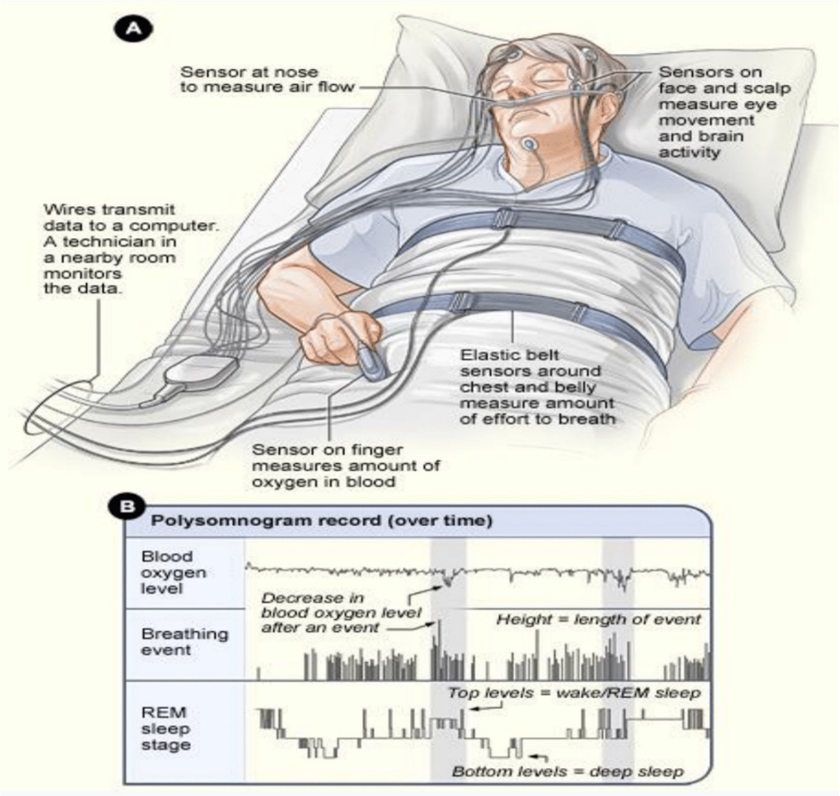
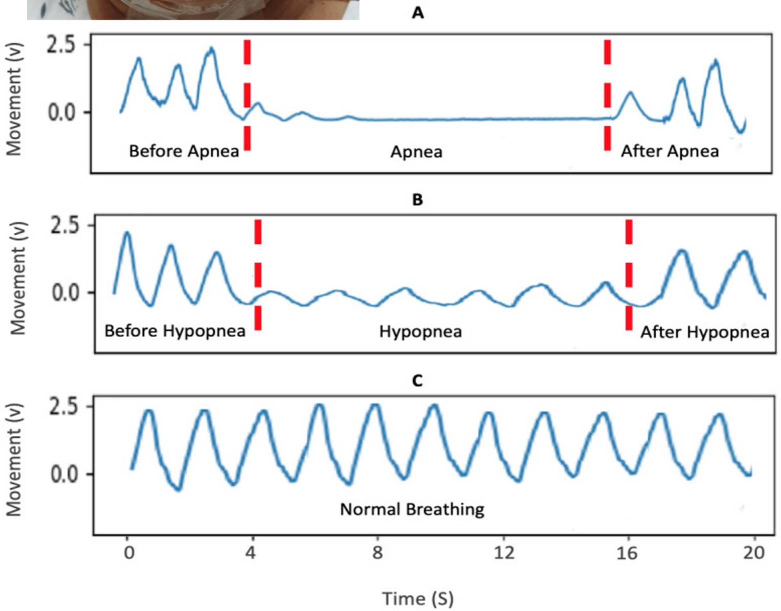
SNU Graduate School of Data Science

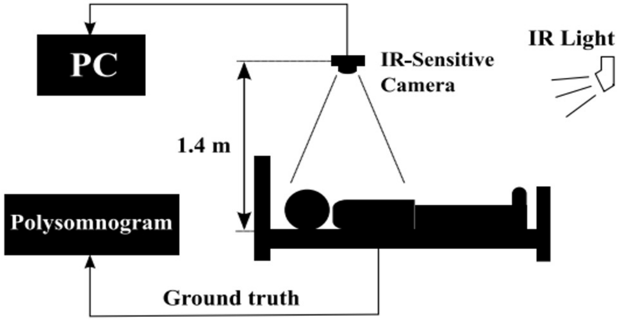
# Table of Contents

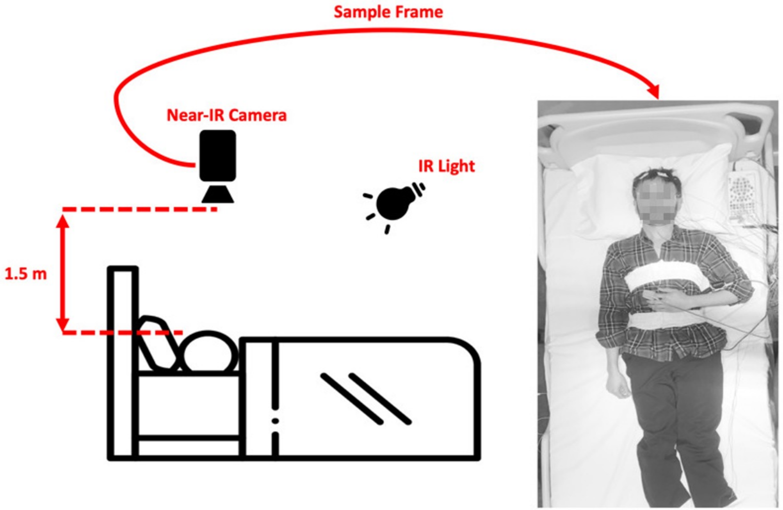
# Definition of Apnea



# Why Baseline model?




T [redacted]
나에게

Hi Jjun,

If I understand correctly, you're asking for the code for our paper. If so, I'm afraid we are unable to share. Our research project was sponsored by an industry partner and they wanted to keep the code private.

I wish you the best of luck.

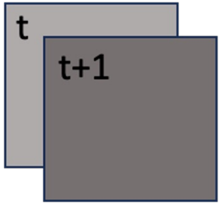
***Apnea** : Cessation of airflow lasting for more than 10 seconds
***AHI** (apnea-hypopnea index) : indicator of the severity of sleep apnea, measures the hourly occurrence rate of apneas and hypopneas

# Data Preprocessing
## : Edit Video Frame

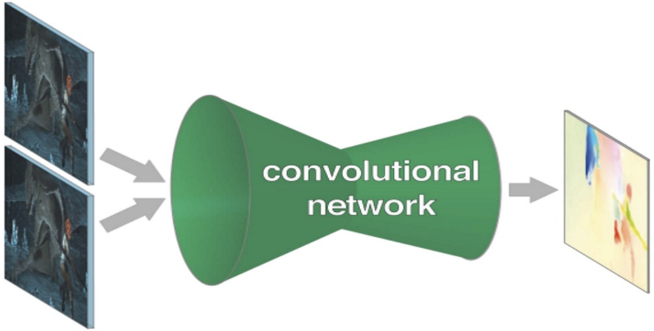
infrared videos : 640×480, 30fps,
5 (±1) hours in a single session

30Hz -> 2Hz downsampling

Extracting frames from video

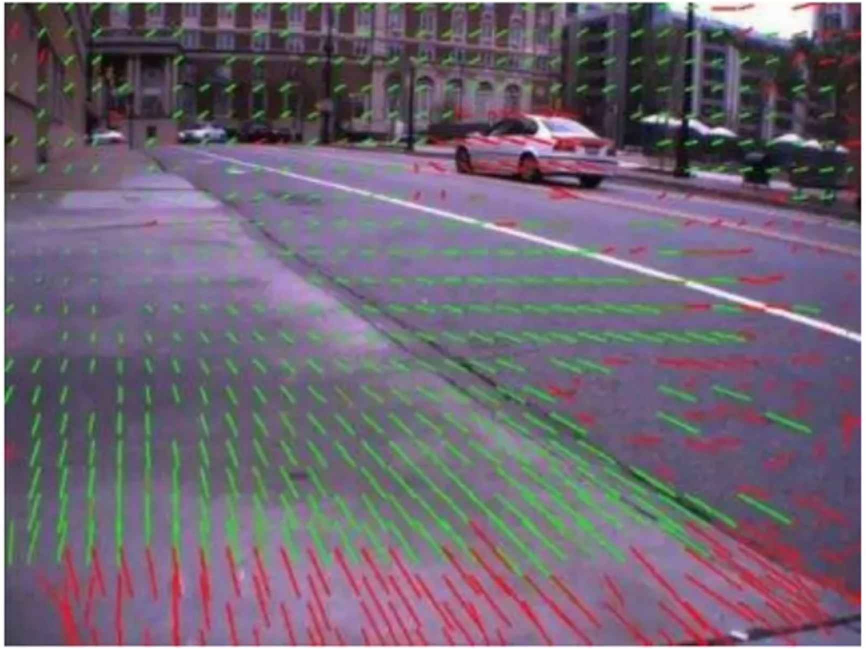


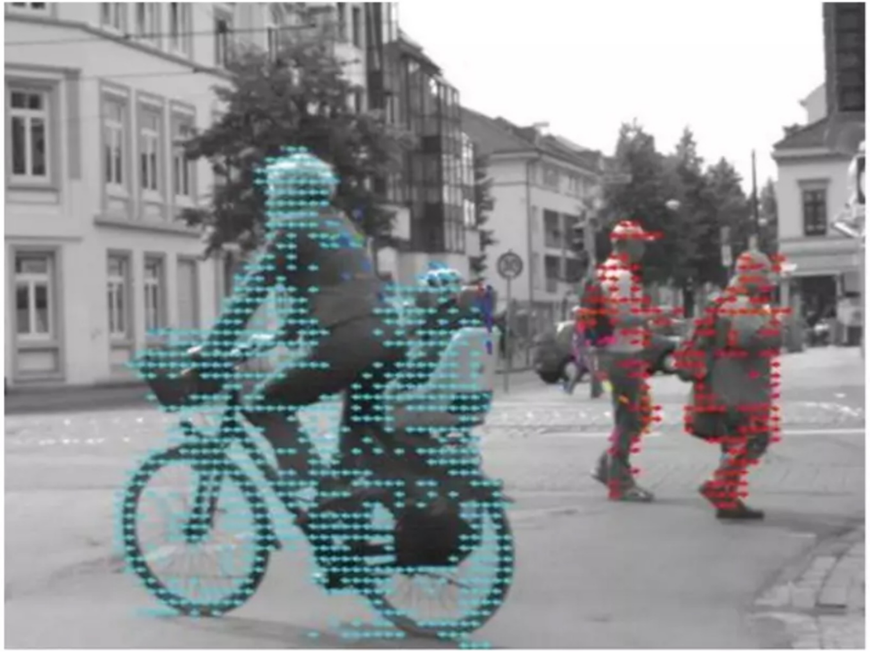

A pair of consecutive frames



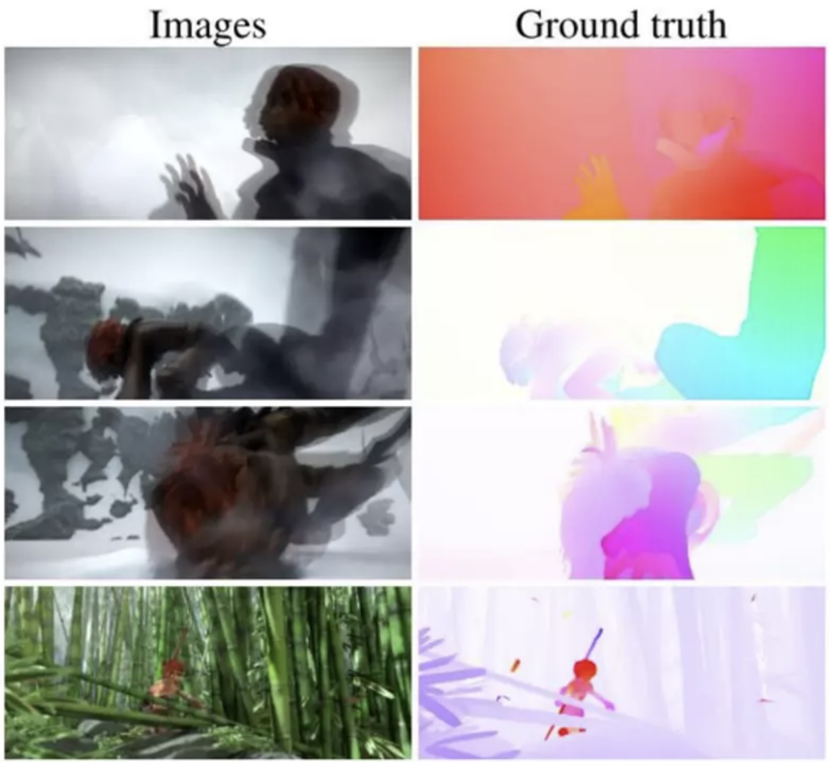
# Optical Flow ?

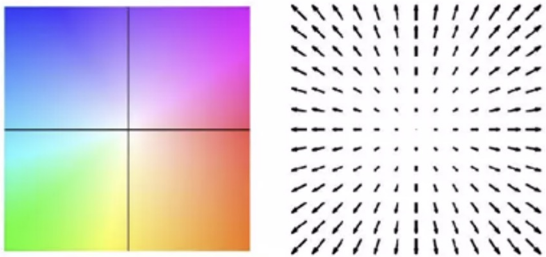
연속한 두 Frame 사이에서 각 Pixel의 Motion을 나타내는 Vector Map (Pixel Displacement)





# Visualizing Optical Flow

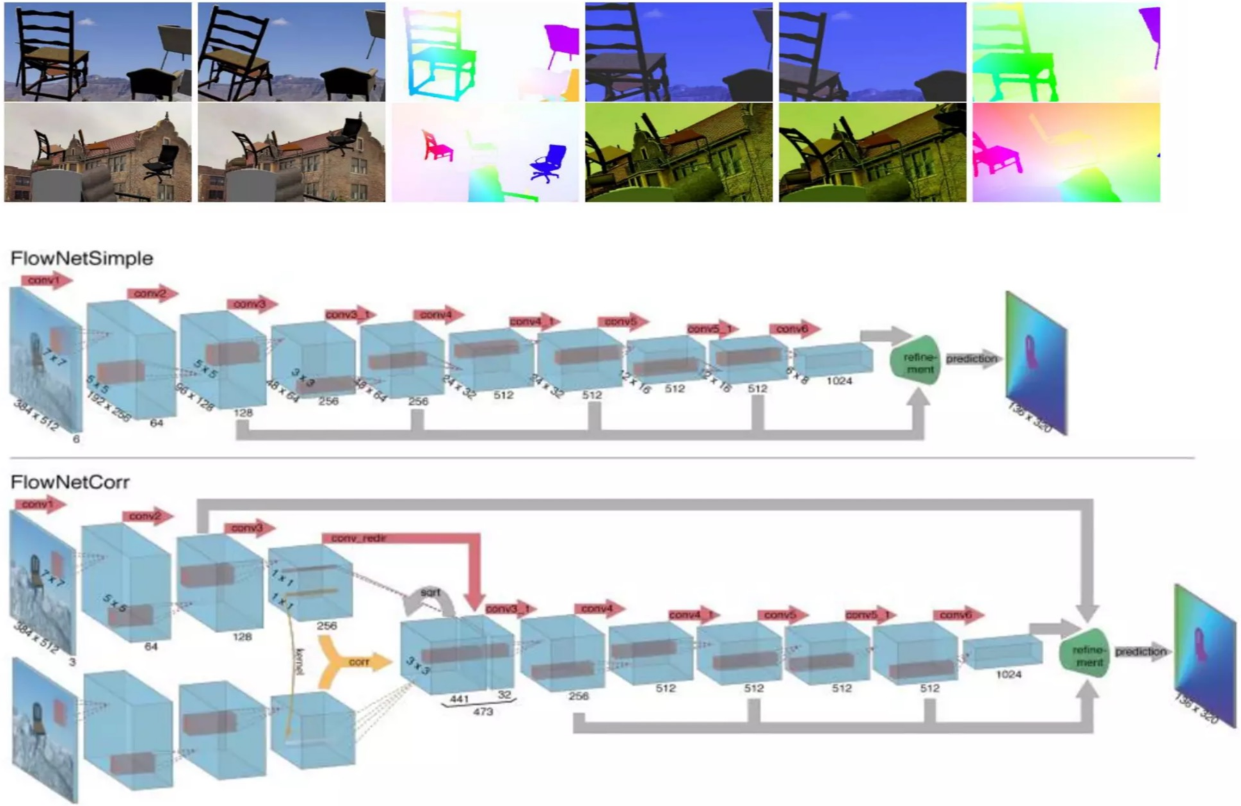


<2-Dimensional Map>

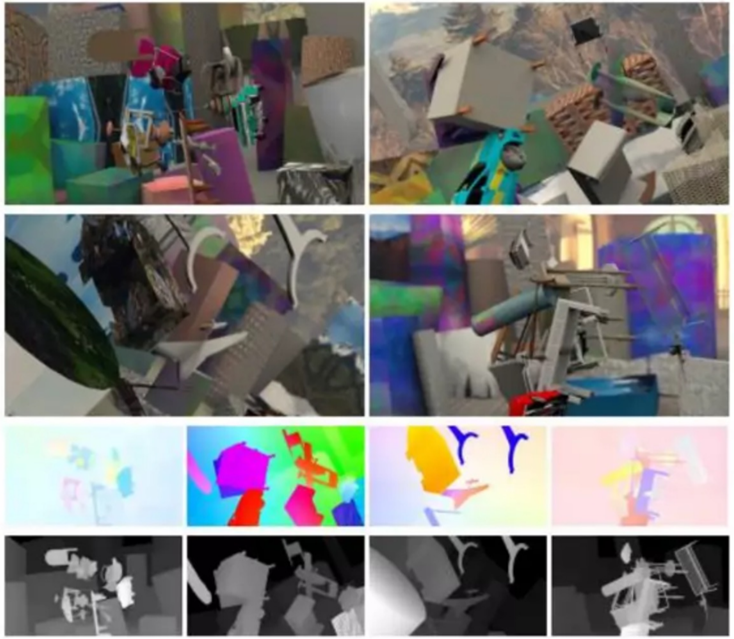
- Color: Direction
- Saturation: Magnitude

# Flownet 1.0

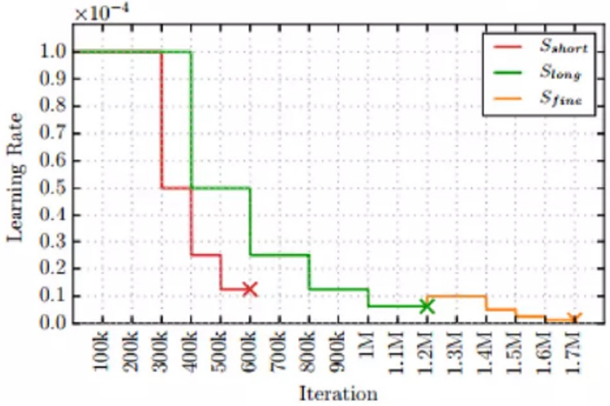

FlowNetSimple
conv1
conv2
conv3
conv3_1
conv4
conv4_1
conv5
conv5_1
conv6
refine-ment
prediction
FlowNetCorr
conv_redir
corr
kernel
441
32
473

# Flownet 2.0

1. Flownet에서 사용한 Flying Chair Dataset으로 Pre-train.
2. Mayer et al. 에서 제안한 Flying Things 3D dataset으로 추가 학습



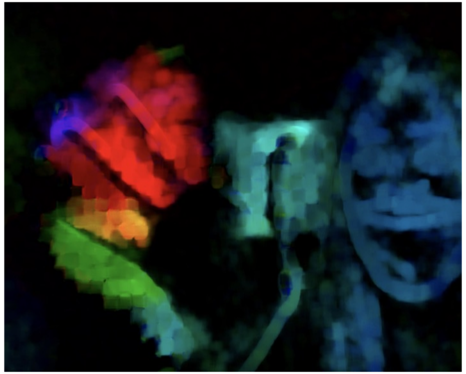
| Architecture | Datasets | $S_{short}$ | $S_{long}$ | $S_{fine}$ |
|---|---|---|---|---|
| FlowNetS | Chairs | 4.45 | - | - |
| | Chairs | - | 4.24 | 4.21 |
| | Things3D | - | 5.07 | 4.50 |
| | mixed | - | 4.52 | 4.10 |
| | Chairs→Things3D | - | 4.24 | **3.79** |
| FlowNetC | Chairs | 3.77 | - | - |
| | Chairs→Things3D | - | 3.58 | **3.04** |



# Experimental

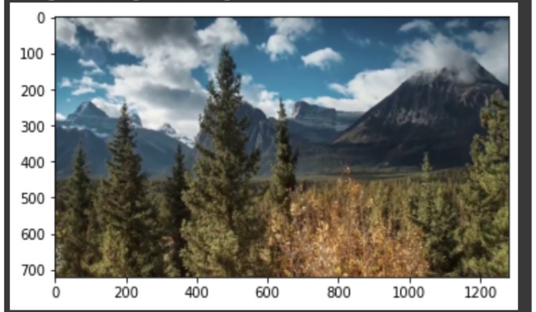
```
nport numpy as np

NKNOWN_FLOW_THRESH = 1e7
ef show_flow(filename):
    """
    visualize optical flow map using matplotlib
    :param filename: optical flow file
    :return: None
    """
    flow = read_flow(filename)
    img = flow_to_image(flow)
    plt.imshow(img)
    plt.show()

ef read_flow(filename):
    """
    read optical flow from Middlebury .flo file
    :param filename: name of the flow file
    :return: optical flow data in matrix
    """
    f = open(filename, 'rb')
    magic = np.fromfile(f, np.float32, count=1)
    data2d = None

    if 202021.25 != magic:
        print ('Magic number incorrect. Invalid .flo file')
    else:
        w = int(np.fromfile(f, np.int32, count=1)[0])
        h = int(np.fromfile(f, np.int32, count=1)[0])
        #print("Reading %d x %d flo file" % (h, w))
        data2d = np.fromfile(f, np.float32, count=2 * w * h)
        # reshape data into 3D array (columns, rows, channels
        data2d = np.resize(data2d, (h, w, 2))
    f.close()
    return data2d

ef flow_to_image(flow):
    """
    Convert flow into middlebury color code image
    :param flow: optical flow map
    :return: optical flow image in middlebury color
    """
    u = flow[:, :, 0]
    v = flow[:, :, 1]

    maxu = -999.
    maxv = -999.
    minu = 999.
    minv = 999.
```

```
import numpy as np
import cv2 as cv

cap = cv.VideoCapture(0)
ret, frame1 = cap.read()
prvs = cv.cvtColor(frame1, cv.COLOR_BGR2GRAY)
hsv = np.zeros_like(frame1)
hsv[...,1] = 255
while(1):
    ret, frame2 = cap.read()
    next = cv.cvtColor(frame2, cv.COLOR_BGR2GRAY)
    flow = cv.calcOpticalFlowFarneback(prvs, next, None, 0.5, 3, 15, 3, 5, 1.2, 0)
    mag, ang = cv.cartToPolar(flow[...,0], flow[...,1])
    hsv[...,0] = ang*180/np.pi/2
    hsv[...,2] = cv.normalize(mag, None, 0, 255, cv.NORM_MINMAX)
    bgr = cv.cvtColor(hsv, cv.COLOR_HSV2BGR)
    cv.imshow('frame2', bgr)
    k = cv.waitKey(30) & 0xff
    if k == 27:
        break
    elif k == ord('s'):
        cv.imwrite('opticalfb.png', frame2)
        cv.imwrite('opticalhsv.png', bgr)
    prvs = next
```

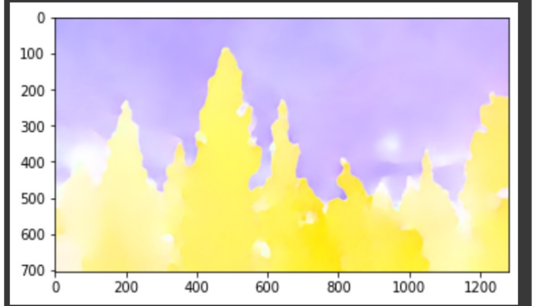


```
1 plt.imshow(tensor_to_image(load_img(frames[1])*255))
```

<matplotlib.image.AxesImage at 0x7f35c001b4e0>




```
1 show_flow(flos[1])
```

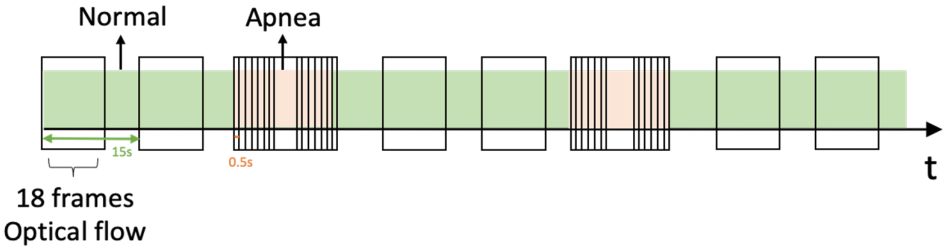


# Training and Test for data

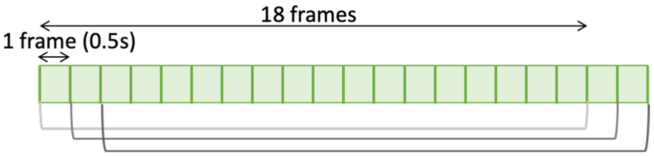
논문 : In training time, to balance the data set, **stride lengths** of **0.5 and 15 seconds** were used for apneas and normal breathing

## Dataset의 불균형을 해결

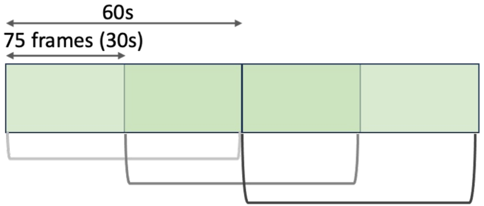
***In training time** stride lengths : 0.5s apnea, 15s normal

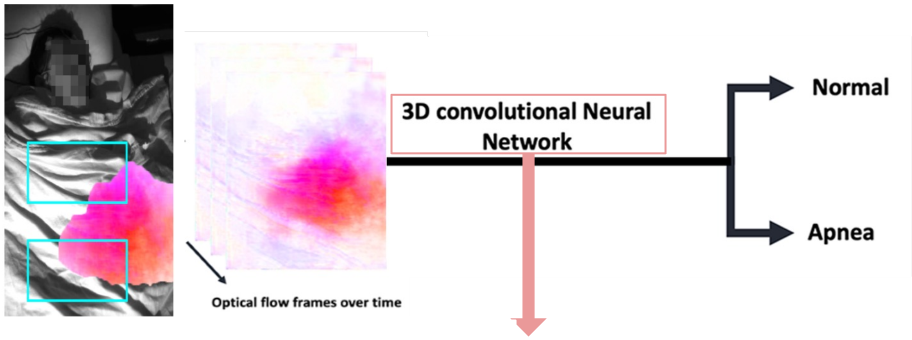



***In test time** 0.5s stride lengths : apnea & normal (2fps)



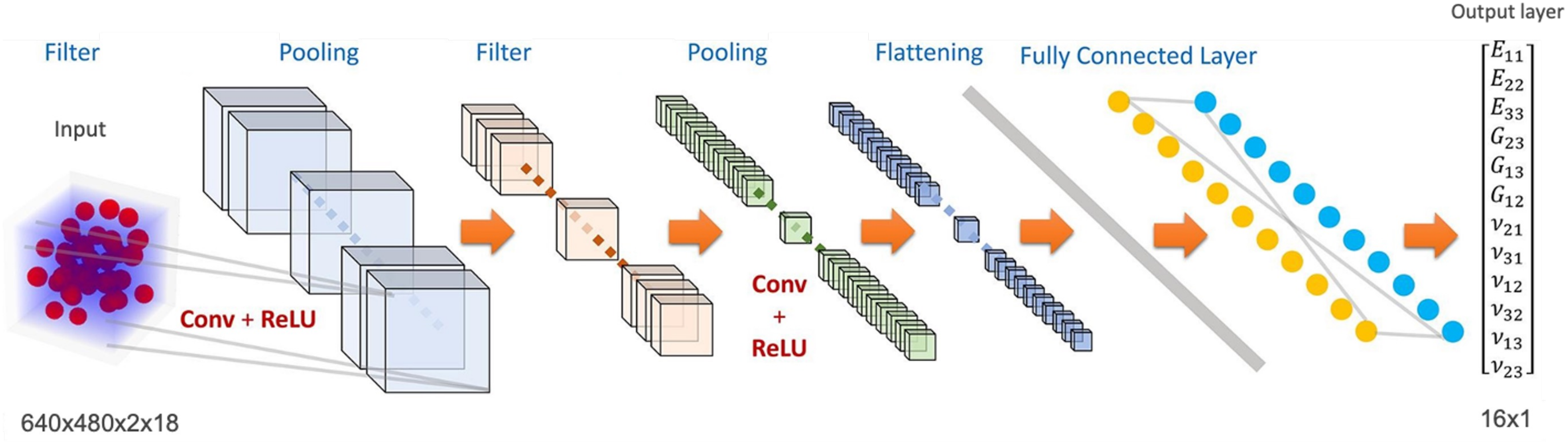

***Our Lab Model** step size : 30s (2.5fps)






## To train 3D-CNN model

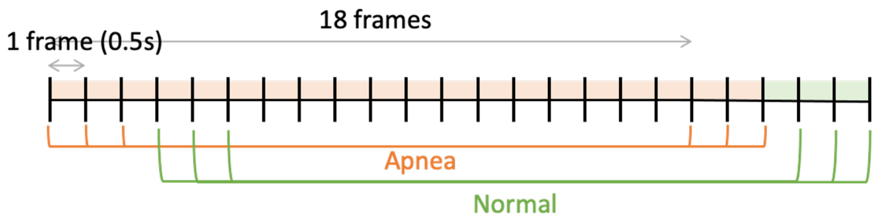
class-weighted cross-entropy loss (5 for events and 1 for normal)
Adam optimizer, Total parameter : 8,284,265
Initial value :  0.001 (Learning rate)
Batch size : 25
Epochs : 25,000
Threshold : 0.1 Trained binary classification (Event vs Normal)

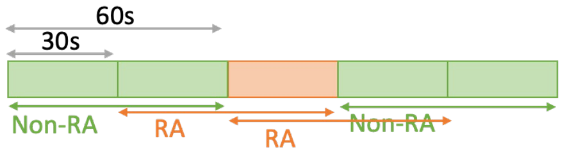


# Using linear regression model
# : for estimate AHI

1) The number of detected events
2) Total duration of detected events longer than 9 seconds / Sleep duration
3) Sleep duration

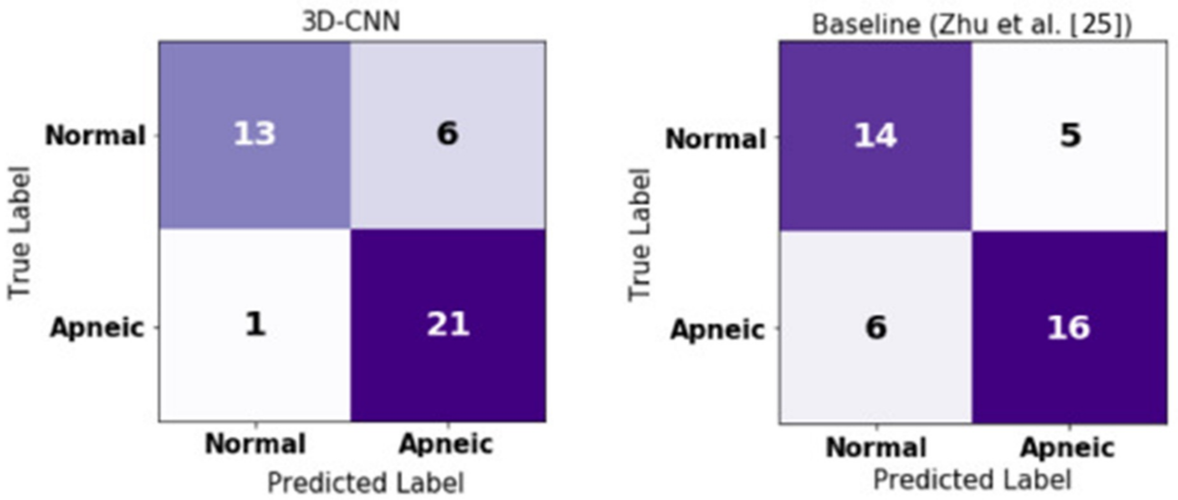
## Apnea count (vs Our Lab Model)

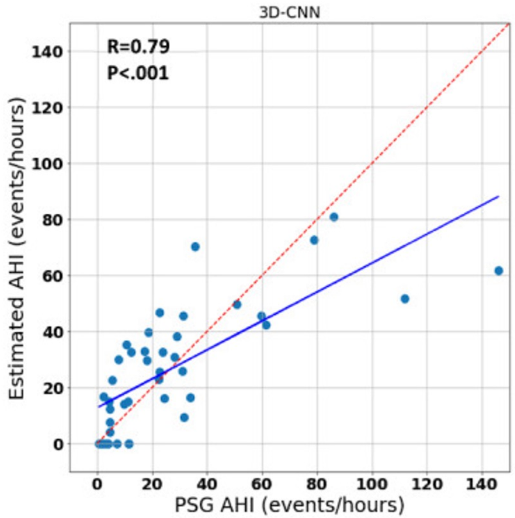



***Respiratory Arousal (RA)**: awakenings that can occur within 3 seconds of an apnea/hypopnea event.

# Confusion matrices ( AHI based screening patients)




| Method | Accuracy | Precision | Recall | F1-score |
| --- | --- | --- | --- | --- |
| 3D-CNN[a] | 82.93 | 77.78 | 95.45 | 85.71 |
| Baseline (Zhu et al [25]) | 73.17 | 76.19 | 72.73 | 74.42 |

Scatterplots of polysomnography (PSG) apnea-hypopnea index (AHI) vs estimated AHI values.
The blue and red lines indicate fitted and unity lines, respectively.

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# Research for Future work
# : Signal to other biological signal

Accepted in AAAI 2021

**CardioGAN: Attentive Generative Adversarial Network with Dual Discriminators for Synthesis of ECG from PPG**

**Performer: A Novel PPG-to-ECG Reconstruction Transformer for a Digital Biomarker of Cardiovascular Disease Detection**

Chu *et al.*
*BMC Medical Informatics and Decision Making* (2023) 23:131
https://doi.org/10.1186/s12911-023-02215-2

BMC Medical Informatics and Decision Making

RESEARCH Open Access

Non-invasive arterial blood pressure measurement and $SpO_2$ estimation using PPG signal: a deep learning framework

# Why There is No Research Estimating Respiratory Rate Based on Other Physiological Data such as PPG or ECG?

**Lack of Information within Physiological Data**
: Signals like PPG and ECG are typically measured using sophisticated devices.

**Complexity -> Simplicity ; Simplicity -> Complexity X**
PPG, ECG data necessitate high accuracy and quality.

**Therefore**, deriving ECG or PPG signals from respiratory signals is not feasible.

**No correspondence** between respiratory signals and other physiological signals derived from them

**How about disease prediction?** -> Combining Respiratory data & SpO2 measurement
=> Respiratory data **alone** as a valuable indicator within the body seems challenging.

# References


Zhu K, Yadollahi A, Taati B. Non-contact apnea-hypopnea index estimation using near infrared video. Annu Int Conf IEEE Eng Med Biol Soc; International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2019; Berlin, Germany. 2019. Jul, pp. 792–795.

Akbarian S, Delfi G, Zhu K, Yadollahi A, Taati B. Automated non-contact detection of head and body positions during sleep. *IEEE Access.* 2019;7:72826–72834. doi: 10.1109/access.2019.2920025.

akkaew P, Onoye T. Non-contact respiration monitoring and body movements detection for sleep using thermal imaging. Sensors (Basel) 2020 Nov 05;20(21):6307. doi: 10.3390/s20216307.

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Li MH, Yadollahi A, Taati B. Noncontact vision-based cardiopulmonary monitoring in different sleeping positions. *IEEE J Biomed Health Inform.* 2017 Sep;21(5):1367–1375. doi: 10.1109/jbhi.2016.2567298.

Saha S, Kabir M, Montazeri Ghahjaverestan N, Hafezi M, Gavrilovic B, Zhu K, Alshaer H, Yadollahi A. Portable diagnosis of sleep apnea with the validation of individual event detection. Sleep Med. 2020 May;69:51–57.

Zhu K, Li M, Akbarian S, Hafezi M, Yadollahi A, Taati B. Vision-based heart and respiratory rate monitoring during sleep – a validation study for the population at risk of sleep apnea. *IEEE J Transl Eng Health Med.* 2019;7:1–8. doi: 10.1109/jtehm.2019.2946147.

CardioGAN: Attentive Generative Adversarial Network with Dual Discriminators for Synthesis of ECG from PPG

Non-Contact Vision-Based Cardiopulmonary Monitoring in Different Sleeping Positions

Non-contact_Apnea-Hypopnea_Index_Estimation_using_Near_Infrared_Video

Extracting_Video-Based_Breath_Signal_For_Detection_of_Out-of-breath_Speech

Contactless Methods For Measuring Respiratory Rate: A Review

# Finally...

Through the CSR workshop, there is an opportunity for a career transition

Physics -> EE ; Next step of becoming a DataScientist

Focus on the Base.. Base..

AI can help make healthcare operations more efficient…

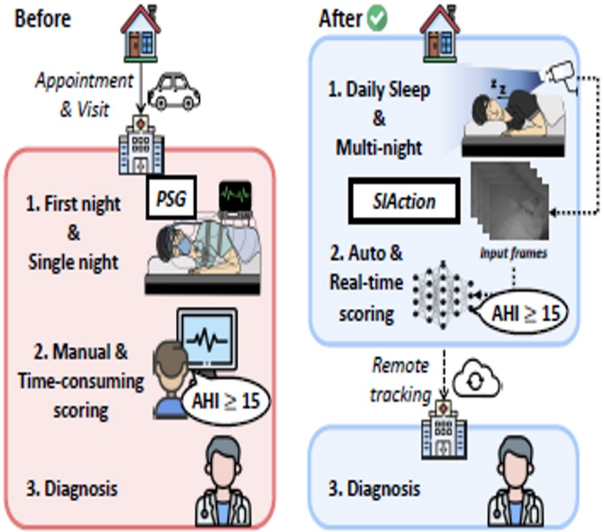


Figure 1: Application scenario of *SlAction*. We envision daily sleep-based early diagnosis of obstructive sleep apnea by addressing various problems in Polysomnography.