WE ARE DEEPMASQUE

We Create Real Masks

TEAM DEEPMASQUE

Interdisciplinary team of data scientists

Data Scientist

Yu-Chieh Lee

- Bachelor of Sci. in EECS
- Incoming Software Engineer at LinkedIn

Data Scientist

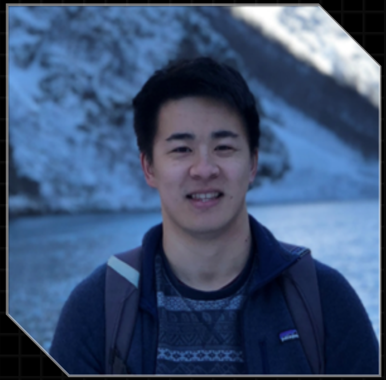
Sierra Park

- Bachelor of Art in Applied Math
- Incoming Data Analyst at Wayfair

Data Scientist

Leo Li

- Bachelor of Art in Cognitive Science
- Bachelor of Art in Statistics



Data Scientist

Chris Chin

- Bachelor of Sci. in Civil Engineering
- Incoming Researcher at MIT

THE GREEN SCREEN TECHNIQUE

A ubiquitous post-production technique

- A green screen is a uniform backdrop used in filming, 3-D printing, and VR
- Allows editors to easily separate the subject from the background to change the background
- Used by everyone from amateur film-ers to Hollywood producers

PROBLEMS

EXPENSIVE,
TIME-CONSUMING,
HIGH BARRIER FOR ENTRY

- Green screen film has to be processed by an editor
- Editing film is expensive, time-consuming, and difficult for beginners
- Is there a better way?

WE CREATE ACCURATE MASKS TO DIFFERENTIATE FOREGROUNDS FROM BACKGROUNDS

++++++

+

FACE

Our mission is to automate the editing process of photos in VR, AR, and entertainment, etc., through precise segmentation via deep learning.

Advisor

Richard Berwick

Richard@twindom.com

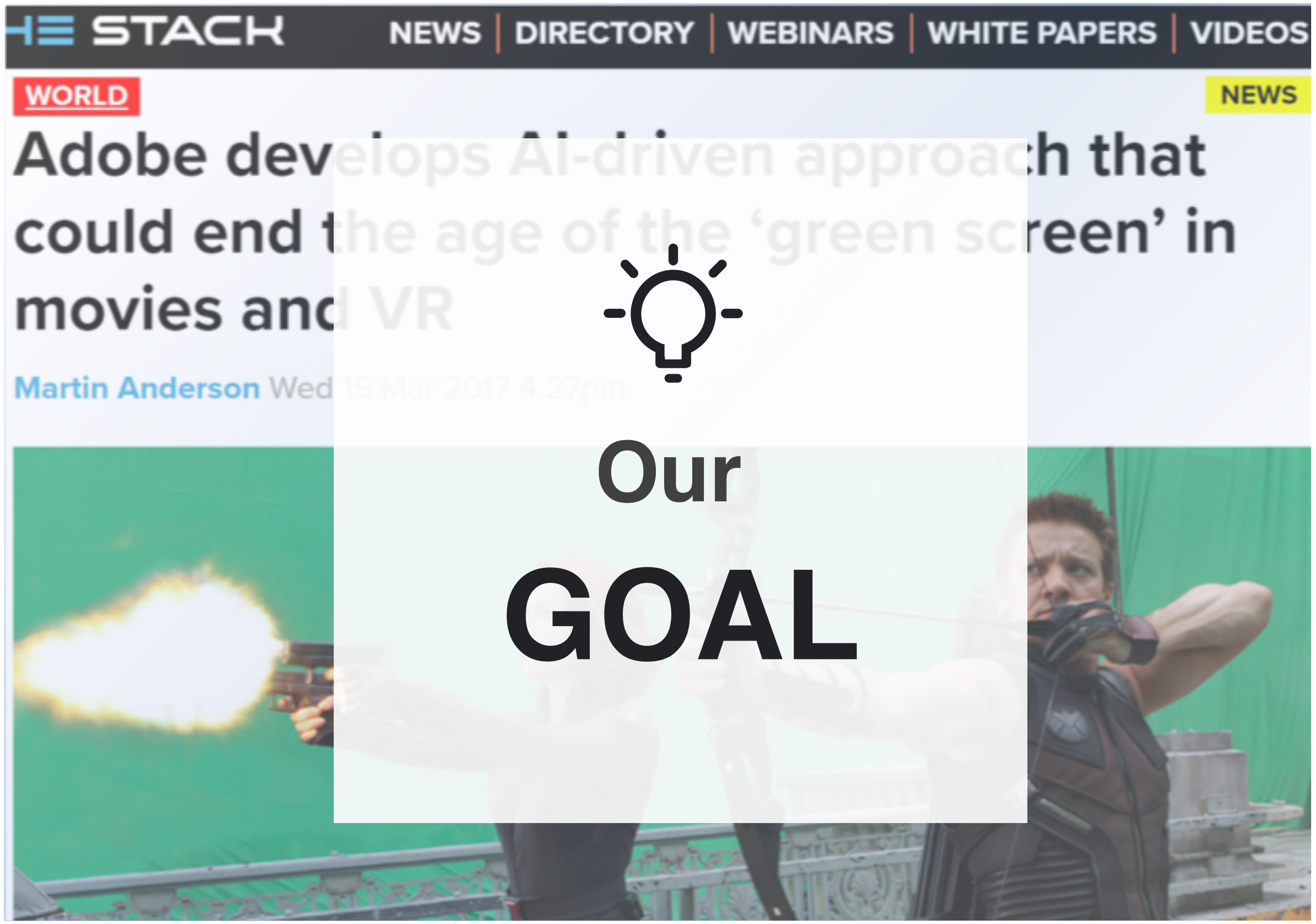
Image, Trimap, Alpha Matte
Portrait FCN+, KNN-Matting
Twindom
>>>>>>>>>>>>>>>>>>>>>>>>

2018/5/2
Product Demo

www.deepmasque.com

ELIMINATE the need for a middle-man

- Make website where users can upload a portrait and instantly separate subject and background
- Enable users to change the background
- Film-makers of any calibre can circumvent the green screen process



OUR ALGORITHM vs MARKET COMPETITORS

Images from one-click background removal websites

01

INPUT IMAGE

02

OUR SEGMENTED IMAGE

03

BURNER.BON-ANZA.COM

04

MALABI.CO

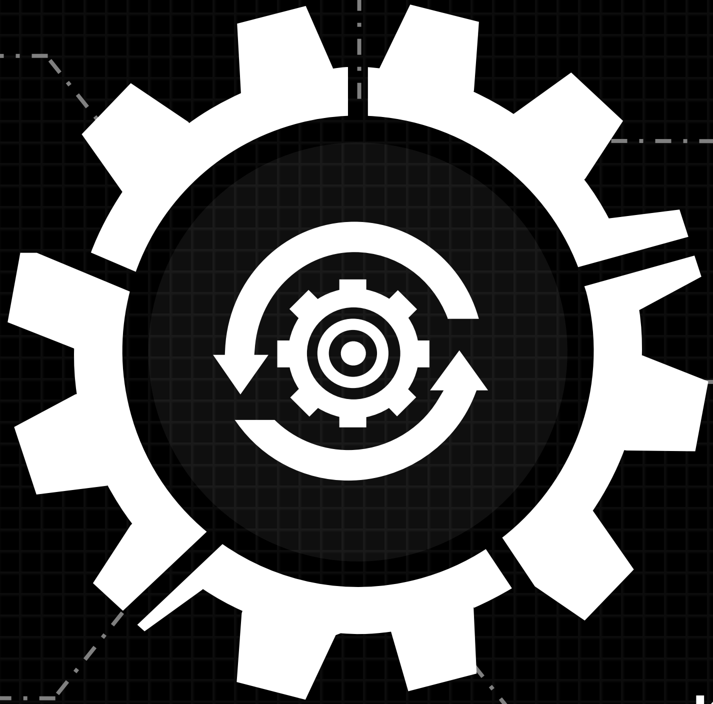
SOLUTION ARCHITECTURE

Pre-processing

- Take in RGB and find facial points by finding offset of x and y components to transform the picture to canonical pose.
- Apply mean mask transform to the image

Portrait FCN+

- Apply VGG on images using multiple smaller convolutional layers/filters for faster computation to capture nonlinearity
- Deconvolution to enlarge the small image back to its original size



Alpha Matte

ResNet

Training deep networks by finding the true y-values by predicting the error from the predicted y-values

Trimap

KNN Matting

User uses K nearest neighbors to get closed-form solution

SOLUTION ARCHITECTURE

Input

Input image of a person

00

SERVER

Amazon EC2 Server

Output

Foreground & Background Segmented

Pre-processing

- Take in RGB and find facial points by finding offset of x and y components to transform the picture to canonical pose.
- Apply mean mask transform to the image

Portrait FCN+

- Apply VGG on images using multiple smaller convolutional layers/filters for faster computation to capture nonlinearity
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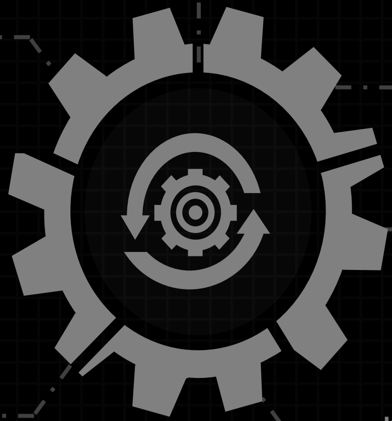


Alpha Matte

ResNet

Training deep networks by finding the true y-values by predicting the error from the predicted y-values

Trimap

KNN Matting

User uses K nearest neighbors to get closed-form solution

OVERVIEW OF SOLUTION

Making the complex seamless

01

INPUT IMAGE

02

TRIMAP

03

ALPHA MATTE

04

COMPOSITE IMAGE

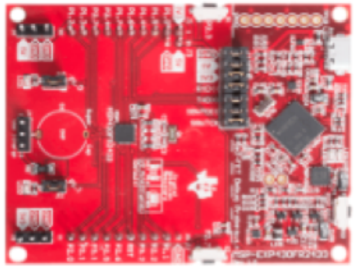
Portrait FCN+
(in TensorFlow)

KNN Matting
& Residual Network

Applying foreground
on another image

A tremendous memory demand reduction compared to state of the art

HARDWARE RESULTS & DEMAND



MSP-EXP430FR2433

- Low cost MSP430 Value Line FRAM MCU LaunchPad.
- Featuring the MSP430FR2433: 16-bit MCU with 16KB FRAM, 4KB SRAM and 10-bit 200KSPS ADC.
- 20-pin LaunchPad kit standard leveraging the BoosterPack ecosystem.
- 2 buttons and 2 LEDs for user interaction.

Capacity: 4 KB

Space Gray

Capacity: 64-256GB

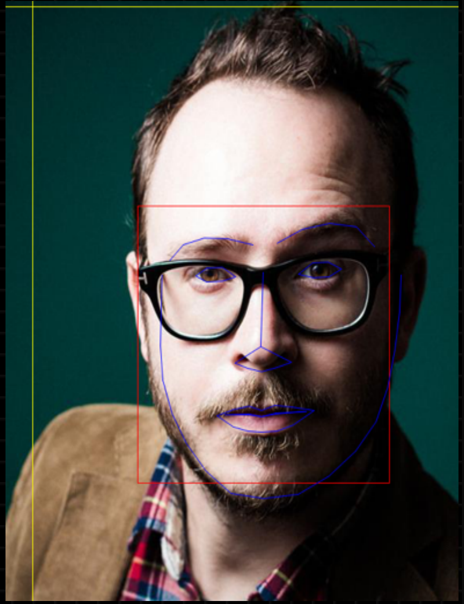
Reduced memory demand by over 2 GB (>> 2 times) with the elimination of DIM acting as middleman between trimap and alpha matte.

FYI: KB = 10^3, GB = 10^9

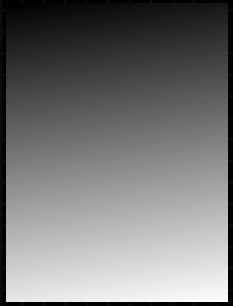
In fact, our trimap to alpha matte algorithm works particularly well due to PortraitFCN+ extreme accuracy in trimap generation and can be implemented on a LaunchPad.

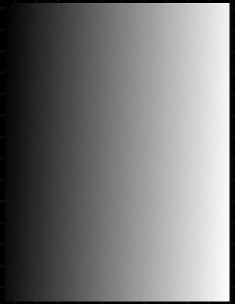
PORTRAIT FCN+: PREPROCESSING

01
INPUT IMAGE



02
DEEP METRIC LEARNING: FACIAL FEATURIZATION

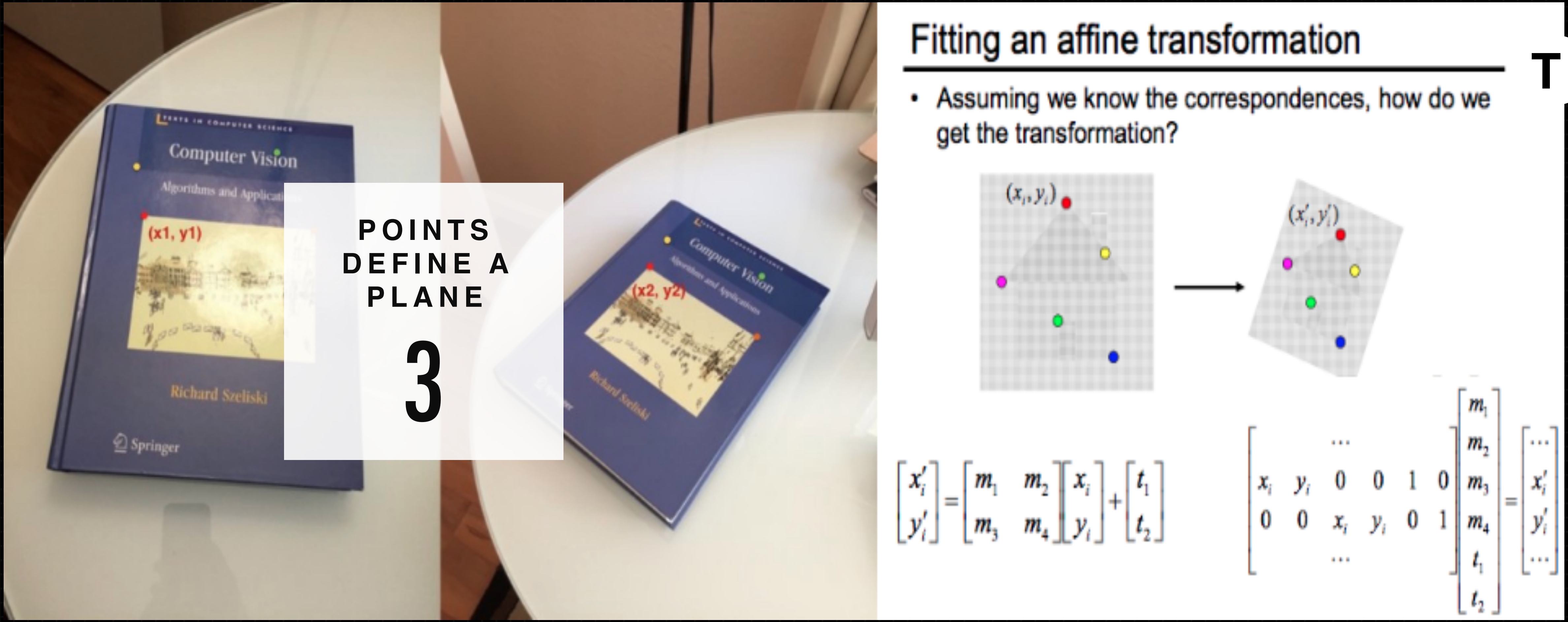




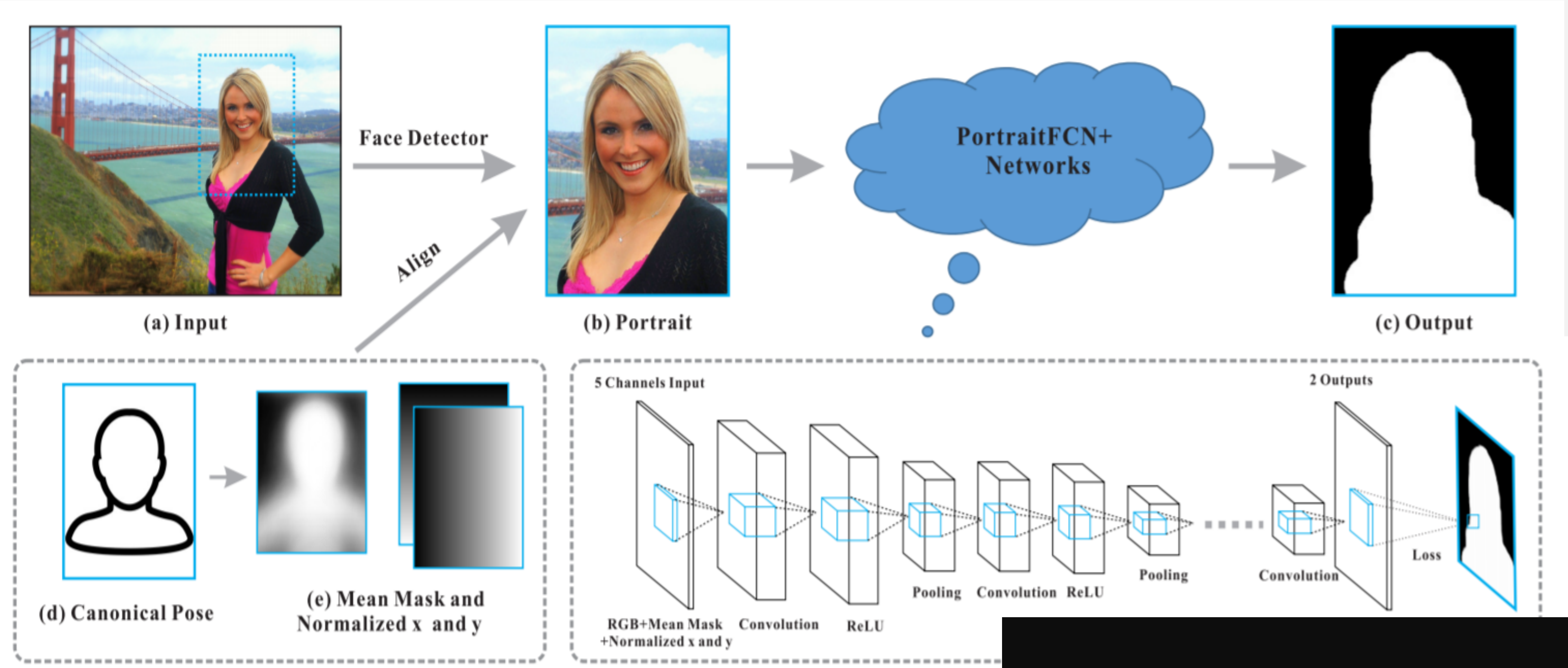
03
MEAN MASK ; YYC; XXC

04
REFERENCE IMAGE

PORTRAIT FCN+: PREPROCESSING



T



From Input to Trimap

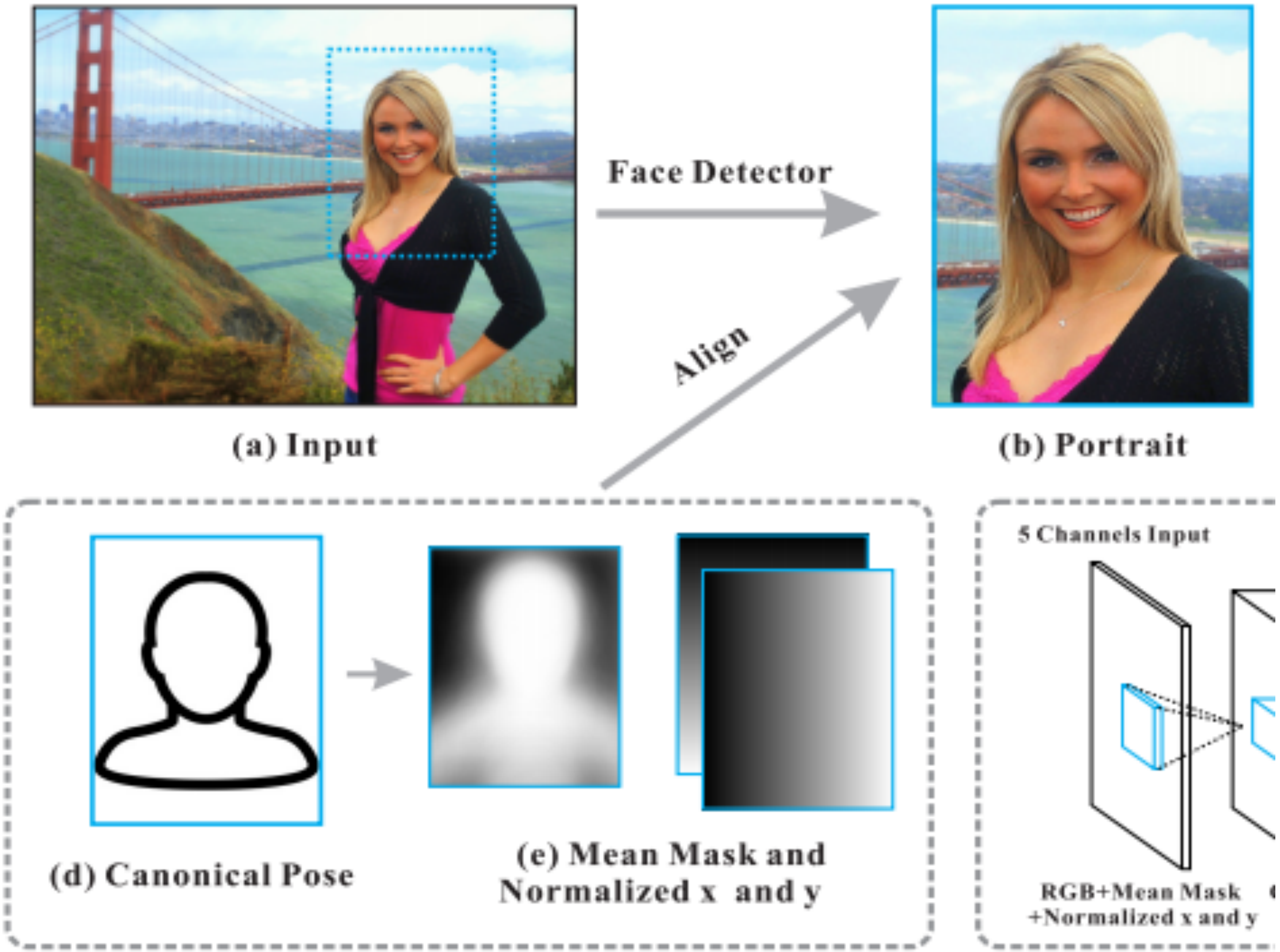
PORTRAIT FCN +

PORTRAIT FCN

+

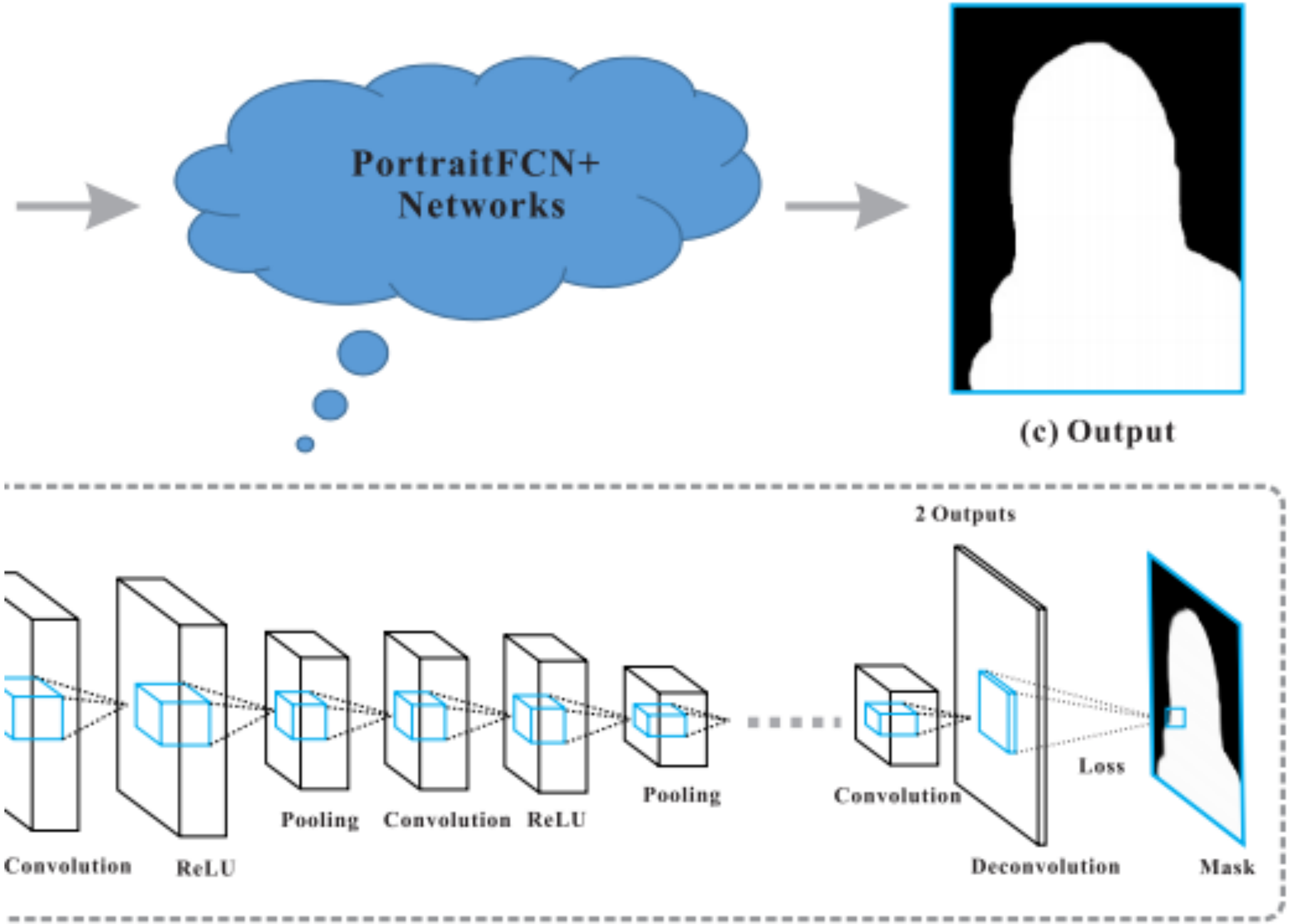
Portrait-specific channels

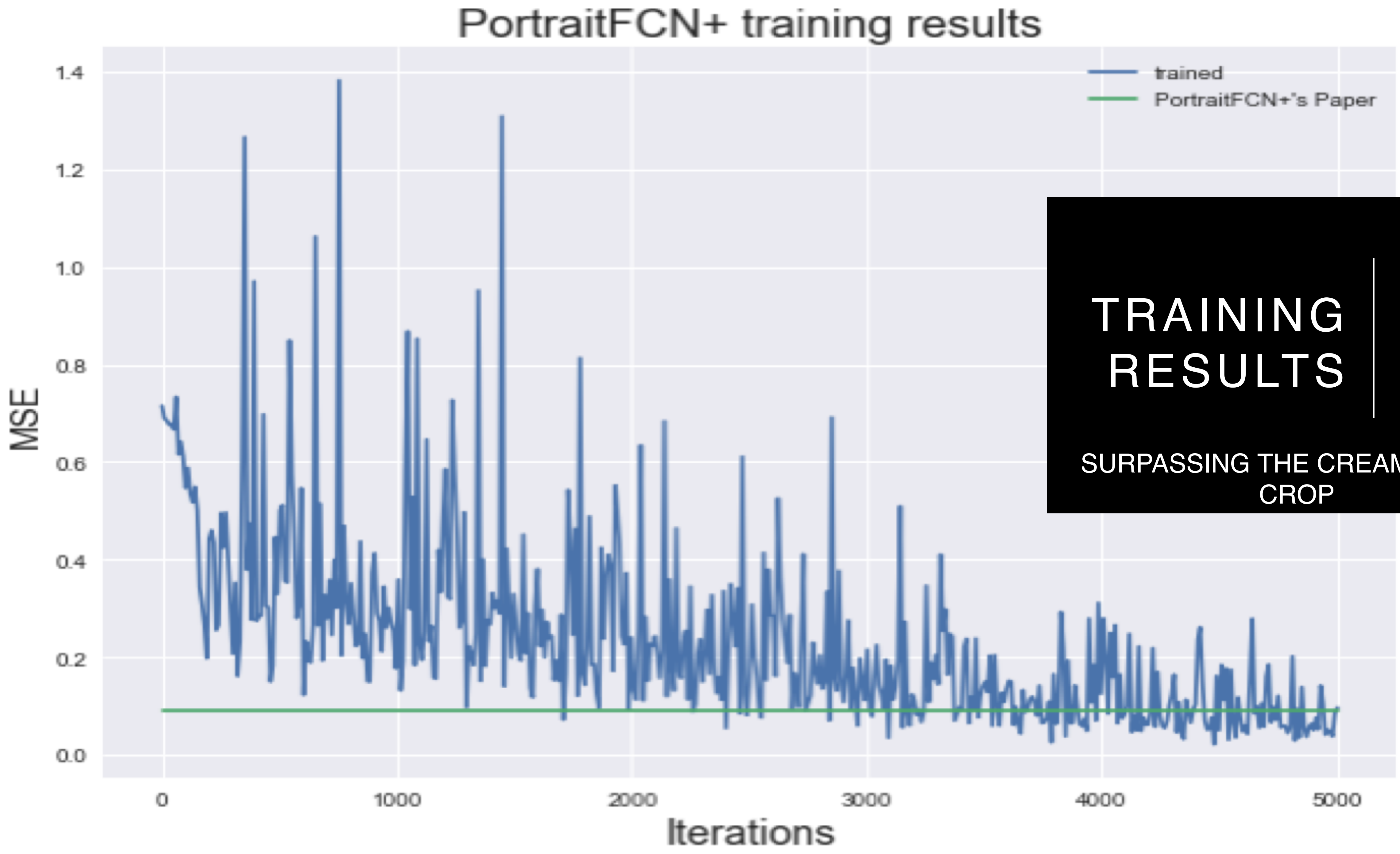
- Augment fully convolutional neural network (FCN) with portrait-specific channels
- Normalized x and y channels: homography transform between facial feature points and canonical pose
- Mean mask channel: subject-shaped region overlaid on actual subject as an estimate of final result



PORTRAIT FCN
+
Layers of the neural network

- Convolution: extract image features, such as edges
- ReLU: nonlinear activation function
- Pooling: max or average of feature over a region
- Deconvolution: upsample previous layers to ensure output matches input size
- Loss: measure error between output and ground truth





TRAINING RESULTS

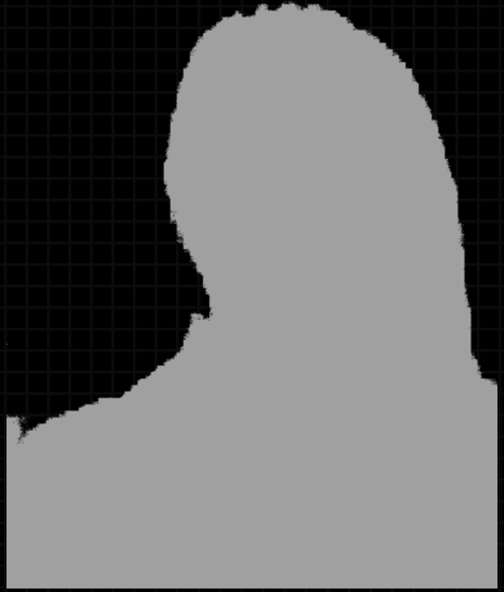
SURPASSING THE CREAM OF THE CROP

TRAINING RESULTS

Comparing to ground truth

01

ORIGINAL



02

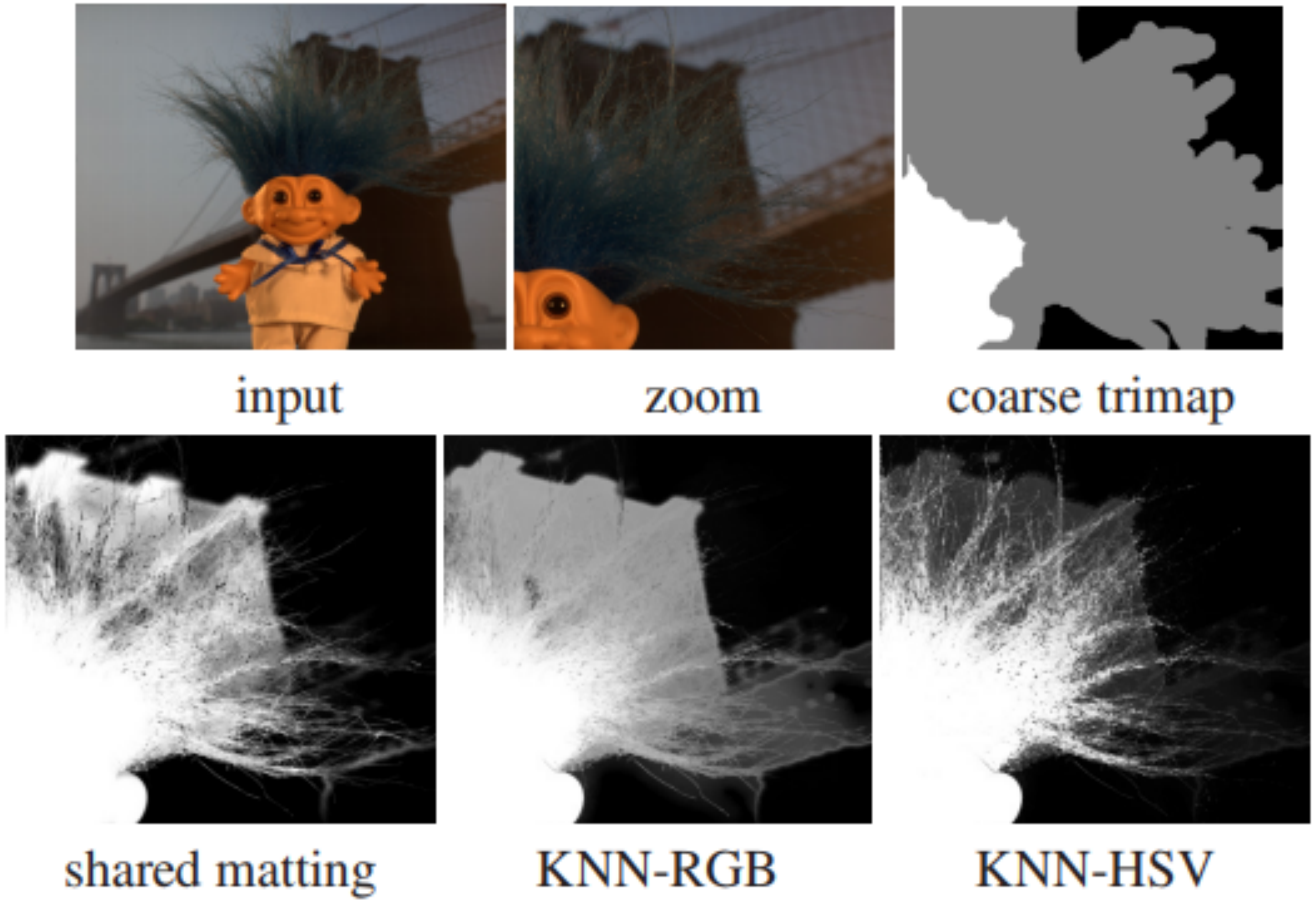
PORTRAIT FCN+ MASK OUR MEAN IOU: 93%

03

PAPER MEAN IOU: 95%

04

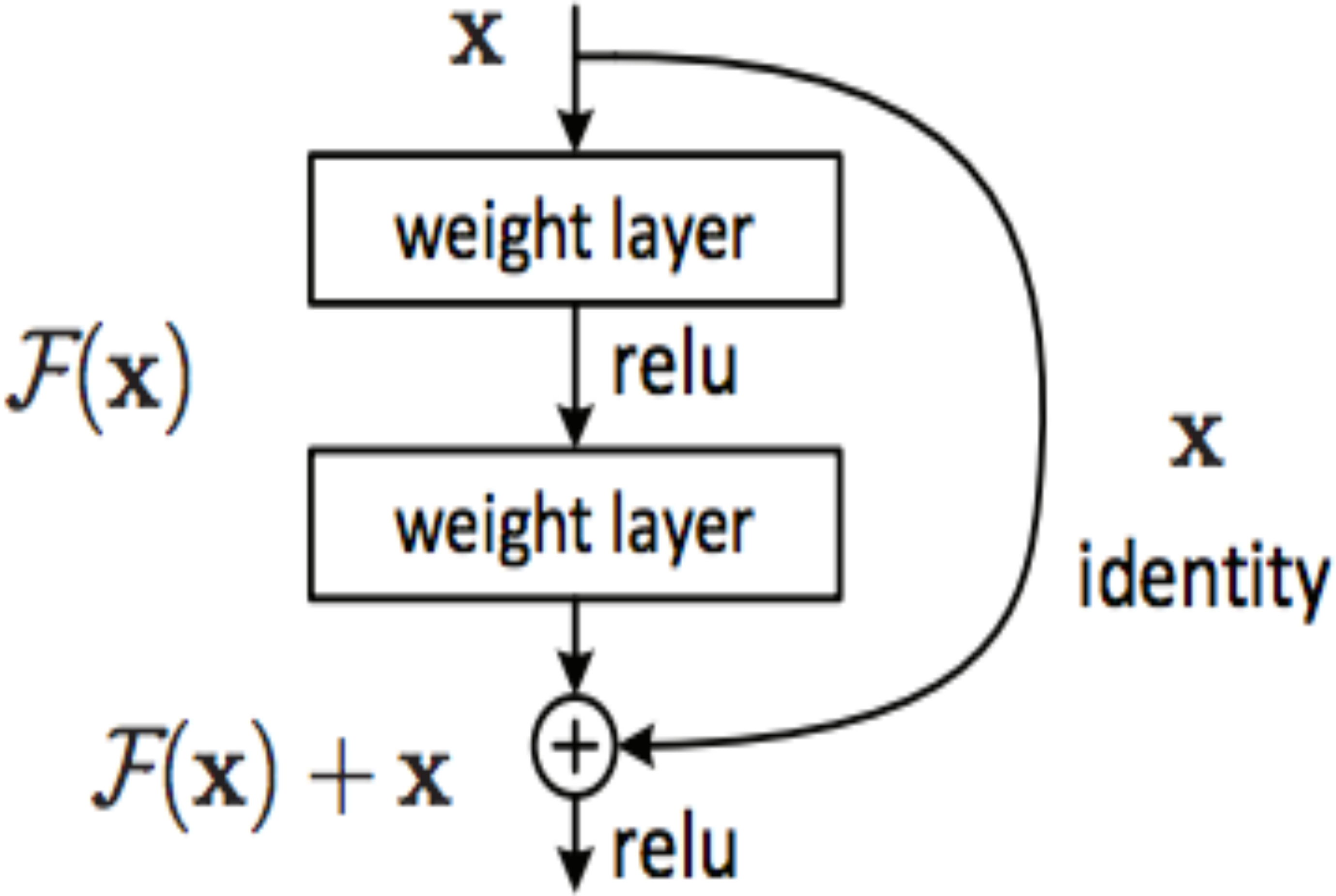
GROUND TRUTH



KNN MATTING

From Trimap to Alpha Matte

- We created trimaps by setting the unknown as 10 pixels away from segmentation boundary of Portrait FCN+
- We then applied it to KNN matting, which uses K nearest neighbours to get closed-form solution
- Closed-form solution utilizes the conjugate gradient method



RESIDUAL NETWORK (RESNET)

Traditionally Used to Avoid Vanishing Gradient, but we use to “refine” alpha matte

- Increased layer of network makes the earlier layers negligible (vanishing gradient)
- Adding the layers leads to high training error
- Imply an identity mapping of the input to create a direct path to the output; the latter layer learns only the residual

KNN MATTING & RESNET Results

From Trimap to Alpha Matte

1 Output of Portrait FCN+ (Mask)

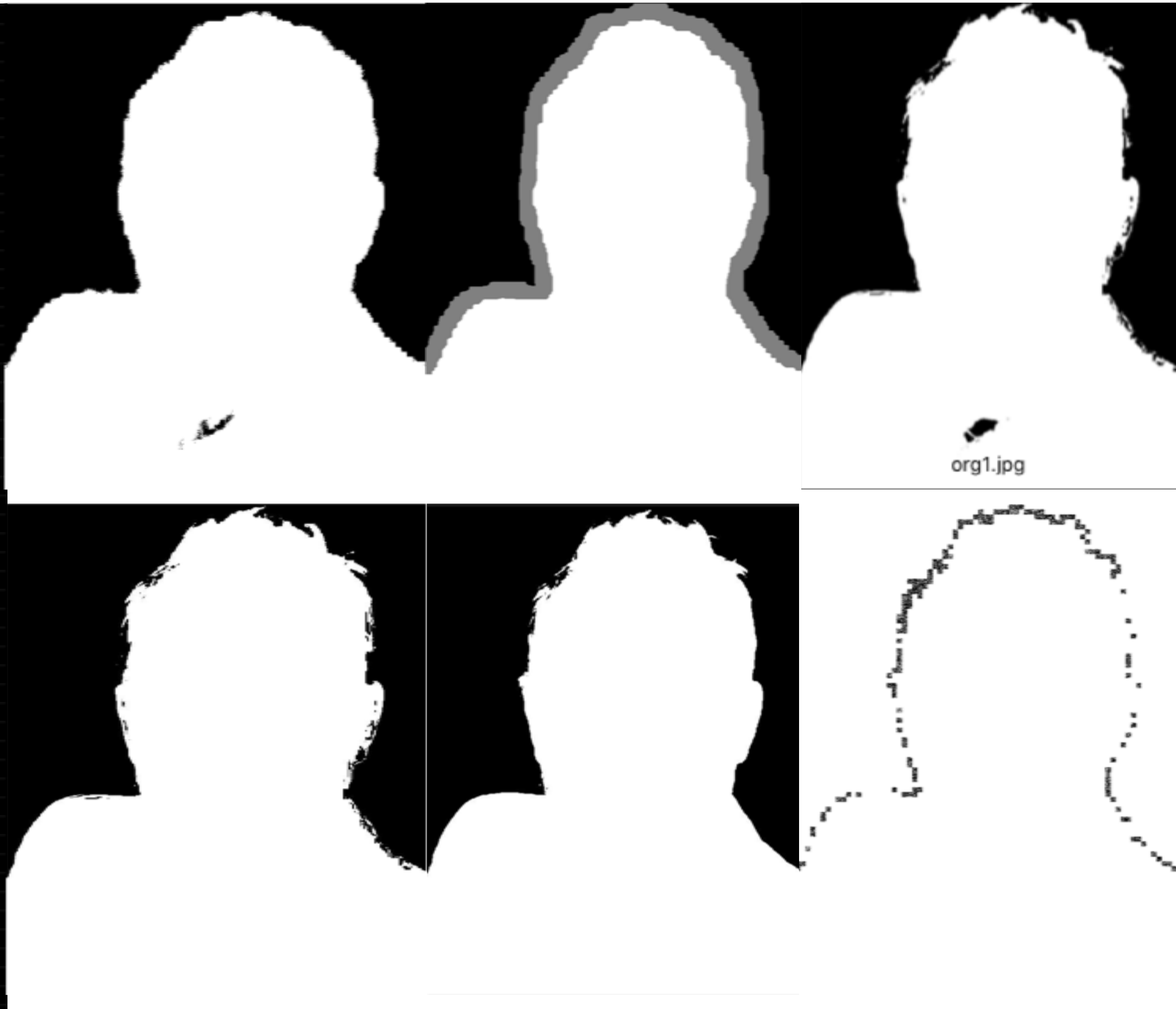
2 Trimap

3 KNN IoU: 95.9%

4 KNN+ Refinement (ResNet) IoU: 97.1%

5 Ground Truth

6 Difference Between 1 & 4



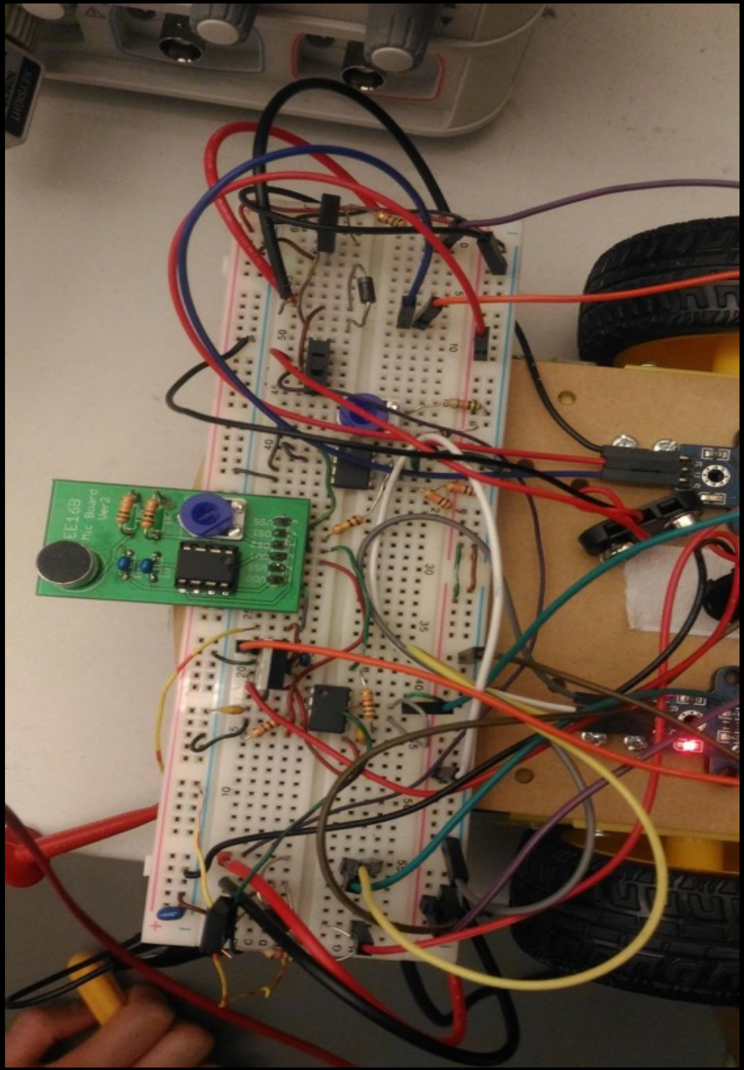
COMPARISON TO DIM (STATE OF THE ART)

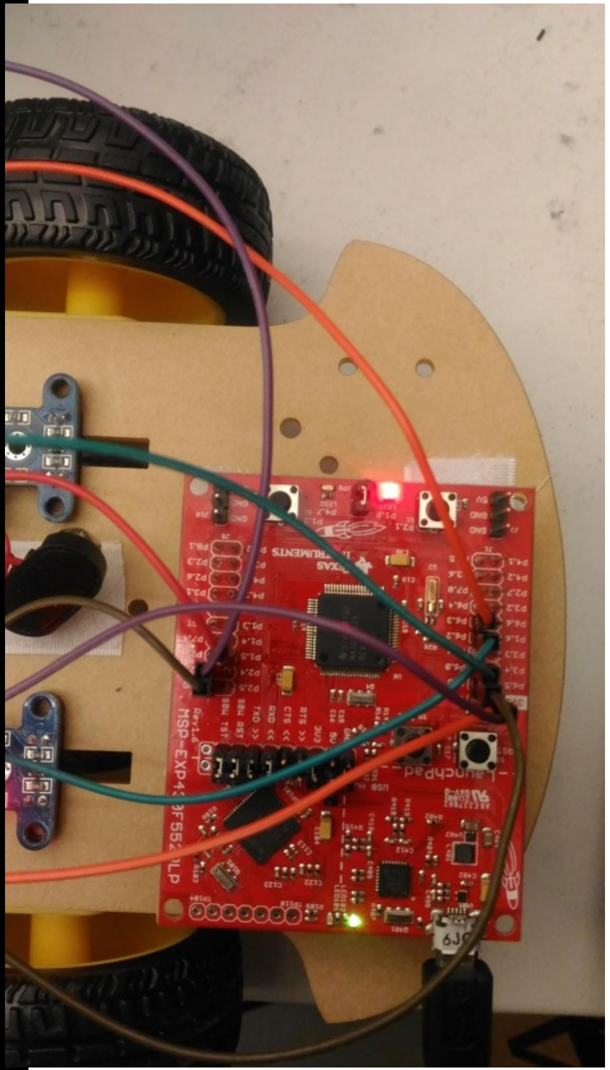
Ours achieved around 97% with KNN

Methods	[13]	[34]	[28]	[16]	[22]	[5]	[8]	Ours
Shared [13]	-	**60.0**	**78.5**	**79.6**	**69.7**	40.6	**57.8**	**83.7**
Learning [34]	40.0	-	**60.2**	**54.6**	**53.4**	27.3	35.1	**83.6**
Comprehensive [28]	21.5	39.8	-	25.8	43.3	20.4	29.2	**78.8**
Global [16]	20.4	45.4	**74.2**	-	**53.3**	30.0	42.0	**84.2**
Closed-Form [22]	30.3	46.6	**56.7**	46.7	-	25.0	38.1	**80.4**
KNN [5]	**59.4**	**72.7**	**79.6**	**70.0**	**75.0**	-	**73.3**	**97.0**
DCNN [8]	42.2	**64.9**	**70.8**	**58.0**	**61.9**	26.7	-	**83.7**
Ours	16.3	16.4	21.2	15.8	19.6	3.0	16.3	-

HARDWARE ADVANTAGE:

KNN-Matting





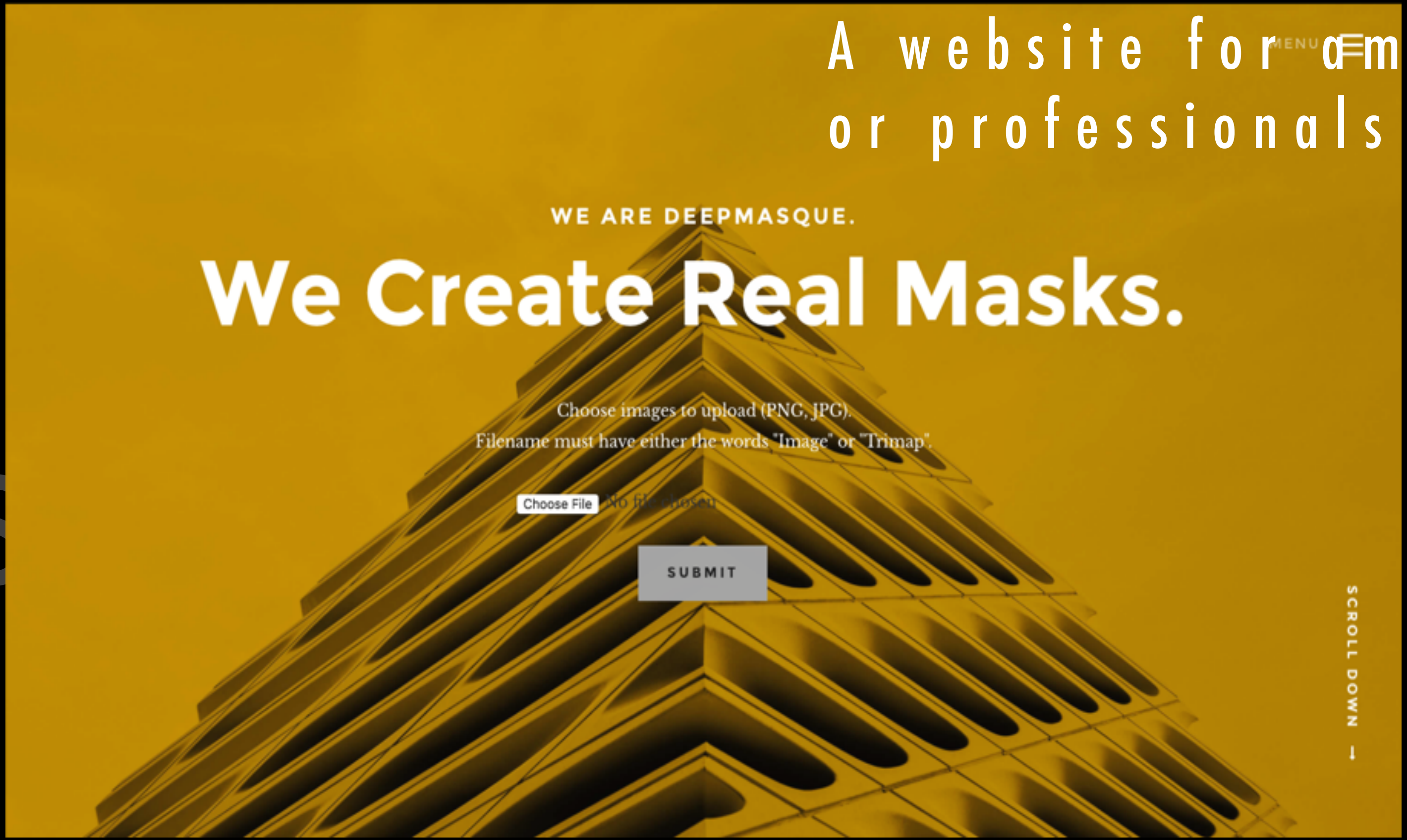
Launchpad: Signal Intake

Applied Signal of length 800 on the micboard which were then projected onto 2 PCA vectors and then applied with KNN as a linear system solver on the spot using a Energia Arduino program. The length 800 voice input represents a column of image which PCA will be applied on.

Significance: We prove that the masking interface for the KNN-matting section is capable of operating on a hardware of only 4 KB, virtually nothing by modern standards. This means we essentially have completely wiped out the original state of the art dependency on memory

USER INTERFACE

A website for amateurs or professionals

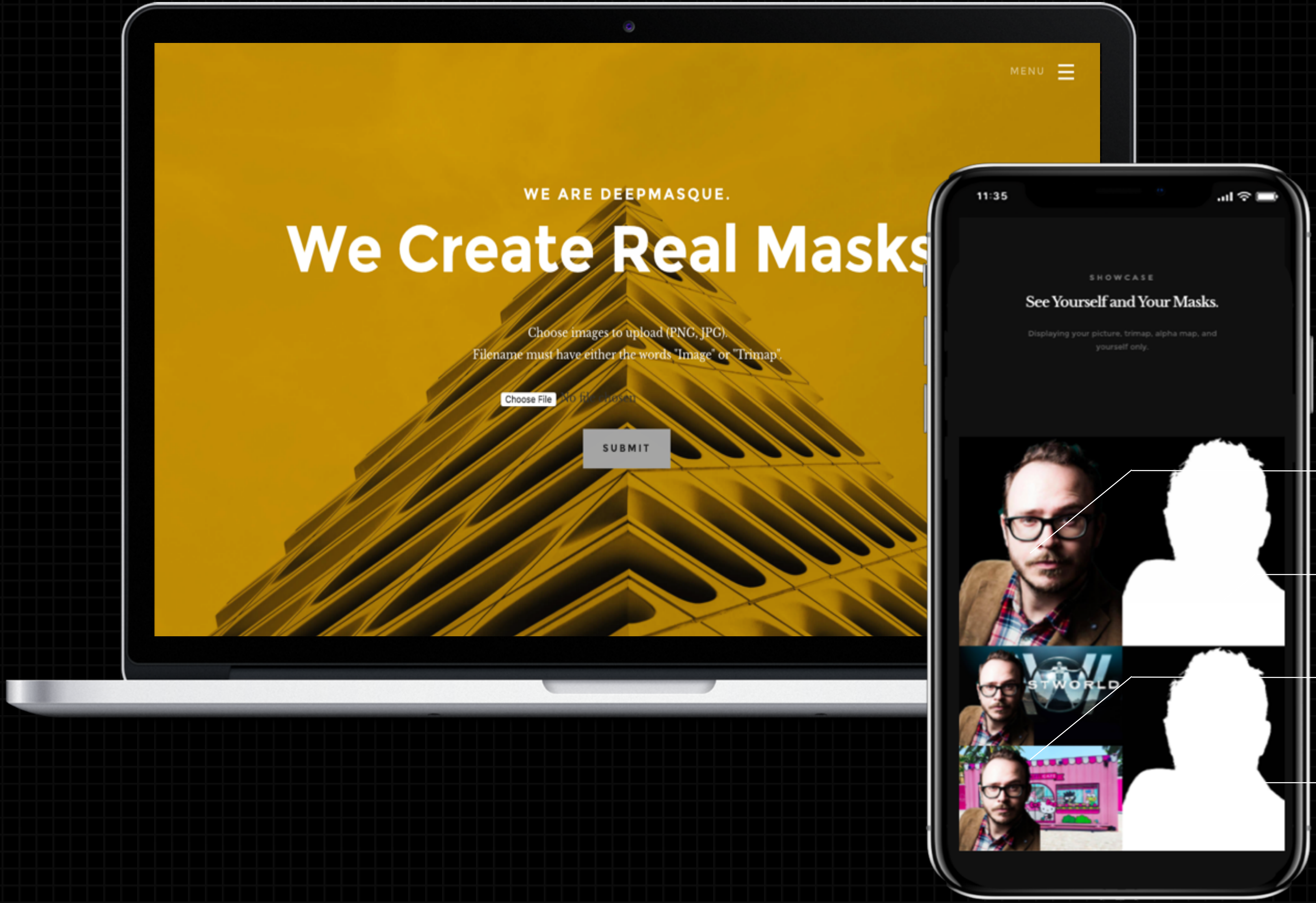


Our website enables the user to upload their picture and submit it to obtain two masks, the trimap and the alpha matte, and a final representation of the subject on a different background.

02

USER INTERFACE

Laptop & Cellphone End



"Our website enables the user to upload their picture and submit it to obtain two masks, the trimap and the alpha matte, and a final representation of the subject on a different background."

01. Original Input Image

02. Trimap

03. Final Products

04. Alpha Matte

... And Beyond

- Use KNN matting to create alpha matte from trimap
- Create user interface in web and mobile development that produces masking images using our model
- Prove the memory reduction of our model compared to planned model with primitive hardware device via hardware demo
  - Achieved similar IoU to DIM with less costly algorithm, opening a potential renew research into KNN-Matting
    - Kept the whole runtime/process time under ~5 minutes (due to KNN unoptimized)
      - Currently working on 3-D Modeling

Low-Tech Demo Goals

- ~~Gain Familiarity with TensorFlow Framework~~
- ~~Develop proficiency in neural networks, CNNs, image segmentation, and FCNs~~
- ~~Understanding two Arxiv papers: 1) Portrait FCN+ 2) Deep Matted Learning Paper~~
- ~~Training datasets for PFCN+ via GPUs (cudas) or AWS (clusters)~~
- ~~Develop Potrait FCN+ and Deep Matted Learning model in Tensorflow~~
- ~~Transform & Present the framework in a user input-allowed format~~

LEARNING PATHS

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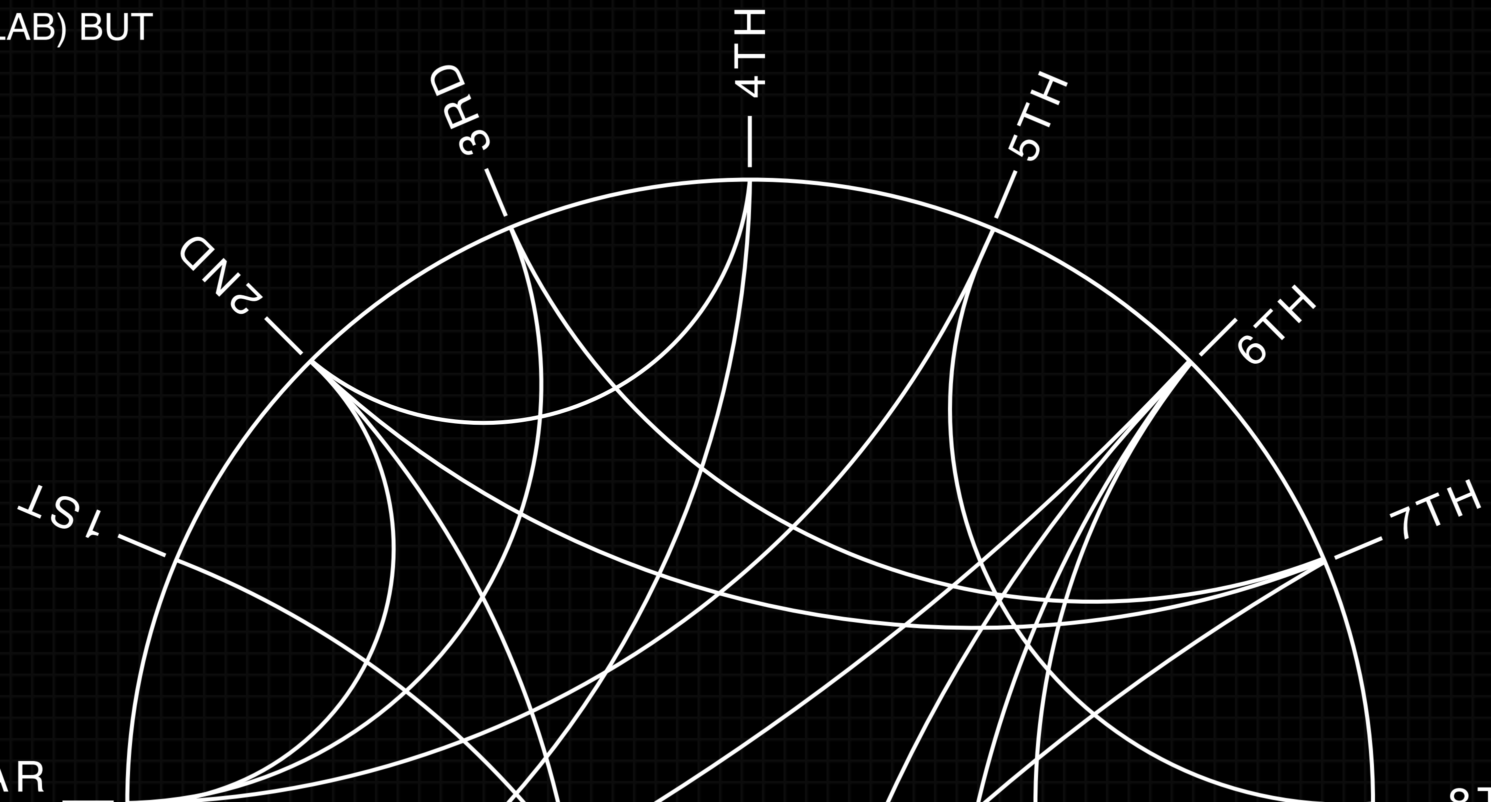
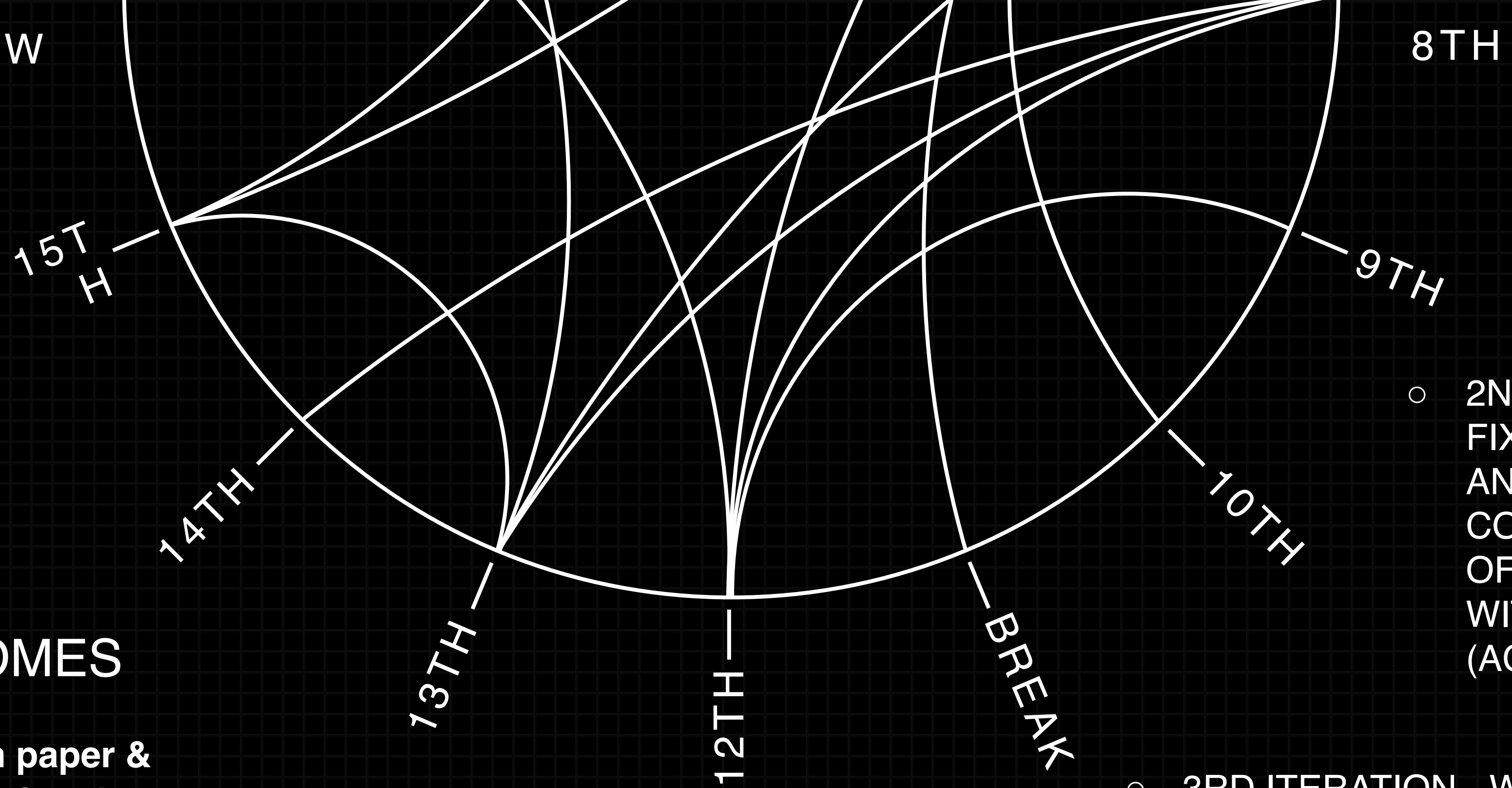
WE STARTED WITH REPRODUCING XIAOYONG SHEN'S PAPER (IN MATLAB) BUT IN TENSORFLOW.

- 0TH POINT: LEARNING TENSOR-FLOW AND DEEP LEARNING/ COMPUTER VISION FOR THE FIRST TIME
  - WE FIRST DID A FCN-8S (USED IN SEGMENTATION FOR SELF-DRIVING CAR) TO SEE HOW THAT WOULD LOOK LIKE. THE LOW IOU WAS ~55%

- 1ST ITERATION - WE THEN IMPLEMENTED PORTRAITFCN+ WHICH HAD MULTIPLE ISSUES:
  - 1) WE DIDN'T SPECIFY PADDING (SO TENSORFLOW JUST MADE THE INCORRECT PADDING FOR US)
  - 2) BUGS WHICH WE FIXED BY USING TF.LAYERS LIBRARY INSTEAD OF TF.NN
  - 3) INCORRECT LOSS FUNCTION AND
  - 4) FAILED TO RUN CAFFE IN TENSORFLOW (WHERE IN PAPER, XIAOYONG & HER TEAM USED CAFFE IN MATLAB) (ACCURACY: 75% IOU)



WE TRIED TRAINING LOCALLY AND THAT FROZE THE LAPTOP, SO WE TRAINED ON 8 CPUS/2 GPUS ON AWS.



01

LEARNING OUTCOMES

- **Analyzing research paper & realizing and validating the implementation of paper**
- **Learned how to use/setup AWS**
- **Learned encoder-decoder network, Resnet, fcn-8s**
- **Computer vision techniques, transforms, Portrait FCN+, KNN application to masking**
- **Basic web development**
- **Facial feature extraction & image rotations**
- **Importance of**

- 2ND ITERATION - FIXED ALL THE BUGS AND INITIALIZE THE CONV-NET PORTION OF PORTRAIT FCN+ WITH VGG (ACCURACY 92%)
- 3RD ITERATION - WE TRAINED THE CONV-NET WITHOUT INITIALIZATION, WHICH DIDN'T CONVERGE (ACCURACY 70% IOU)
  - WE RECEIVE A REPLY FROM THE DIM PEOPLE THAT THEIR DATA CANNOT BE USED FOR ANY COMMERCIAL PURPOSES, WHICH COMPLICATED OUR MENTORSHIP WITH TWINDOM.
- 4TH ITERATION - WE REALIZED THAT PORTRAIT FCN+ MIGHT WORK WELL WITH KNN-MATTING. IMPLEMENTED THE KNN-MATTING.

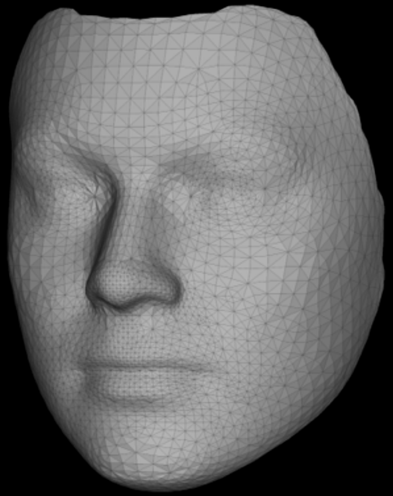
- 5TH ITERATION - ADDED RESNET AND SOME POST-PROCESSING TO IMPROVE IOU (96% IOU)
- IMPLEMENTED ***TWO*** ITERATIONS OF UI

Future Work

3D Morphable Face Model

Isomap texture extraction

- to obtain a pose-invariant representation of the face texture
- Linear scaled orthographic projection camera pose estimation
- Linear shape-to-landmarks fitting
- Expression fitting, and 6 linear expression blendshapes
- Edge-fitting, heavily inspired



Surrey Morphable Face Model

Surrey Face Model is a PCA model of shape variation built from 3D face scans. It comes with uv-coordinates to perform texture remapping

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