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Supplemental material: Realistic Facial Age Transformation with 3D Uplifting

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This supplementary material contains more details on the neural networks and displays results with high resolution.

A. Neural Network Details

Here, we introduce the network architectures of *SkinNet*, *GeoNet*, and *RefineNet* in detail, as well as the training process of the whole pipeline.

• **SkinNet** consists of *PredNet* and *ReconNet*. Given an input image, *PredNet* estimates the concentrations of two chromophores (melanin and hemoglobin). The structure of *PredNet* is shown in Table 1. *PredNet* consists of 4 fully connected layers. The outputs of *PredNet* are fed into *ReconNet* to reconstruct re-aged skin appearances. The structure of *ReconNet* is shown in Table 2. Similarly, *ReconNet* consists of 4 fully connected layers. Each fully convolution layer, except the last layer in both networks, is followed by a ReLU [Aga18].

Table 1: *PredNet architecture*

Layer	Input Size	Output Size
Fully Connected	3	64
Fully Connected	64	64
Fully Connected	64	64
Fully Connected	64	2

Table 2: *ReconNet architecture*

Layer	Input Size	Output Size
Fully Connected	2	64
Fully Connected	64	64
Fully Connected	64	64
Fully Connected	64	3

• **GeoNet** has a similar structure as Decoder of [RBSB18]. As shown in Table 3, *GeoNet* consists of a fully connected layer to convert the size of the latent space, including shape (β), expression (ψ), pose (θ) and age (a) parameters, for further reconstruction. After the fully connected layer, *GeoNet* contains five blocks to reconstruct a 3D face shape. Each block includes an Up-Sampling layer and a Chebyshev Convolution layers [DBV16] with $K = 3$ Chebyshev polynomials, and an Exponential Linear Unit(ELU) [CUH16]. The Up-Sampling layer aims to increase the vertices number to around 4 times. The loss function of this part is shown in Equation 3 in the main paper, where $\lambda_v = 1.0$, $\lambda_{pho} = 0.2$, $\lambda_{age} = 0.05$, and $\lambda_{reg} = 0.1$.

Table 3: *GeoNet architecture*

Layer	Input Size	Output Size
Fully Connected	160	5 × 128
Up-Sampling	5 × 128	20 × 128
Chebyshev Convolution	20 × 128	20 × 128
Up-Sampling	20 × 128	79 × 128
Chebyshev Convolution	79 × 128	79 × 64
Up-Sampling	79 × 64	314 × 64
Chebyshev Convolution	314 × 64	314 × 16
Up-Sampling	314 × 16	1256 × 16
Chebyshev Convolution	1256 × 16	1256 × 16
Up-Sampling	1256 × 16	5023 × 16
Chebyshev Convolution	5023 × 16	5023 × 3

• **RefineNet** is a light weight network to extract the high frequency information as displacement map. This network only contains two convolution layers. The first convolution layer is followed by a ReLU [Aga18]. The kernel, stride and padding of each convolution layer is 3, 1, and also 1, respectively. The loss function of the *RefineNet* is shown in Equation 5 in the main paper, where $\lambda_{pho} = 1.0$, $\lambda_{dx} = 0.1$, and $\lambda_{dy} = 0.1$.

The **Training process** of the whole pipeline is we first trained *SkinNet* separately on Lookup Tables generated by the skin model [LGLG24], and trained *AgeEditNet* separately on Facescape dataset and Lifespan datasets. Furthermore, we fixed the *SkinNet* and *AgeEditNet*, and trained *GeoNet* to obtain coarse shapes following by fixing these three and trained *RefineNet* as a whole pipeline.