

Comparison of Default Patient Surface Model Estimation Methods

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Introduction

• Patient Surface Model

Triangle mesh describing the geometry of the surface of a patient (Fig. 2)

• Associated Clinical Applications

Patient positioning relative to imaging device [1][2]
dose estimation [3]

Methods

• General Formulation

$$\hat{x} = \mathcal{F}(X, g)$$

\hat{x} : surface model estimates $\hat{x} \in \mathbb{R}^{3N}$

\mathcal{F} : mapping function

X : set of 3D scans of human subject $X \in \mathbb{R}^{3N \times M}$

g : underlying measurements of human subjects

• Linear Regression

Estimate a regression matrix A as the linear mapping between patient measurement and associated mesh.

$$\hat{x} = Ag \quad A = XG^+ \quad G: \text{set of measurements}$$

• Kernel Principal Component Analysis

Introduce non-linear mapping using a Gaussian or linear kernel function Φ_* .

$$\hat{x} = Ac(g) \quad c_i = \sum_{k=1}^M \alpha_{i,k} \Phi_*(g, g_k)$$

$$\Phi_{\text{GK}}(g, g_k) = \exp\left(-\frac{\|g-g_k\|^2}{2\sigma^2}\right) \quad \Phi_{\text{LK}}(g, g_k) = g^T g_k$$

• Active Shape Model

Learn the joint subspace representation c between surface mesh and associated patient measurements [4].

$$x = \bar{x} + Q_s c \quad g = \bar{g} + Q_m c$$

• Deep Neural Network

Train a deep neural network (Fig. 1) to find the non-linear mapping between measurements and principle component of associated surface mesh [5].

$$x = \bar{x} + Q_s \mathcal{F}^{\text{DNN}}(g)$$

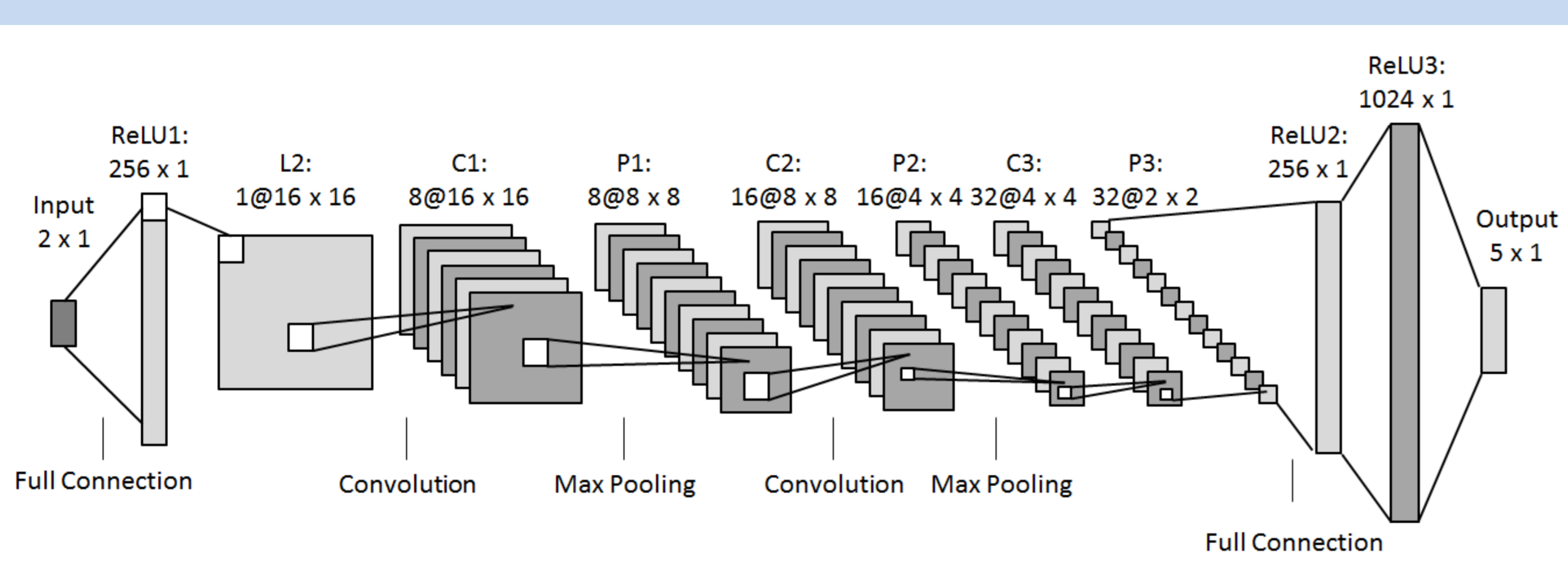


Figure 1: An illustration of the proposed regression network topology. Input parameters are height and weight. Two deep neural networks were set up, one for meshes associated with women, another one for meshes representing men.

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Evaluation

• Dataset

865 male and 1063 female surface meshes with associated height and weight measurements.

• Training

Separate training for male and female model using 90% of the associated dataset. The remaining 10% is used as test set.

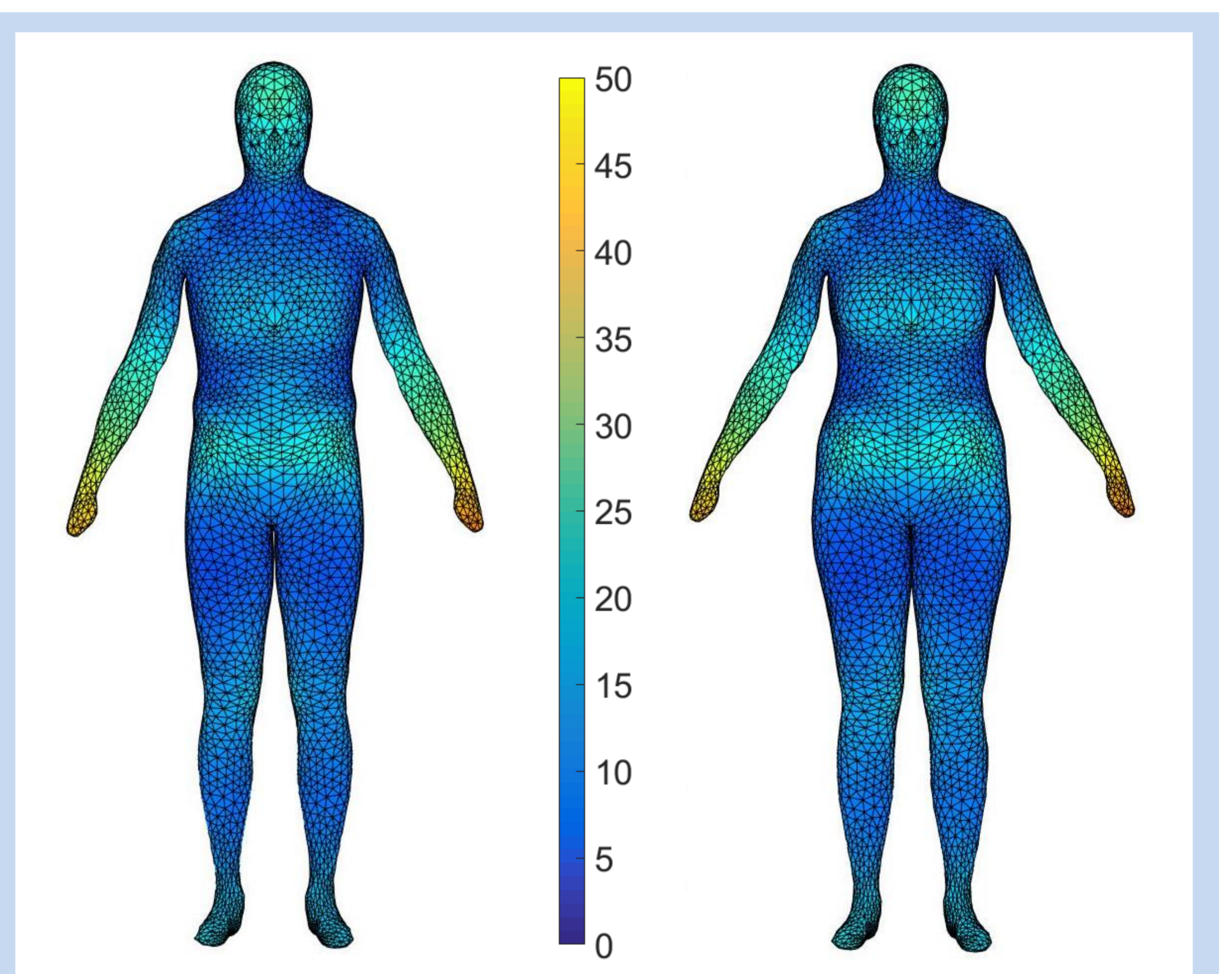


Figure 2: Surface model estimation mean vertex error of male (left) and female (right) in mm using deep neural network. The largest estimation errors are found in the hand and arm regions due to pose differences.

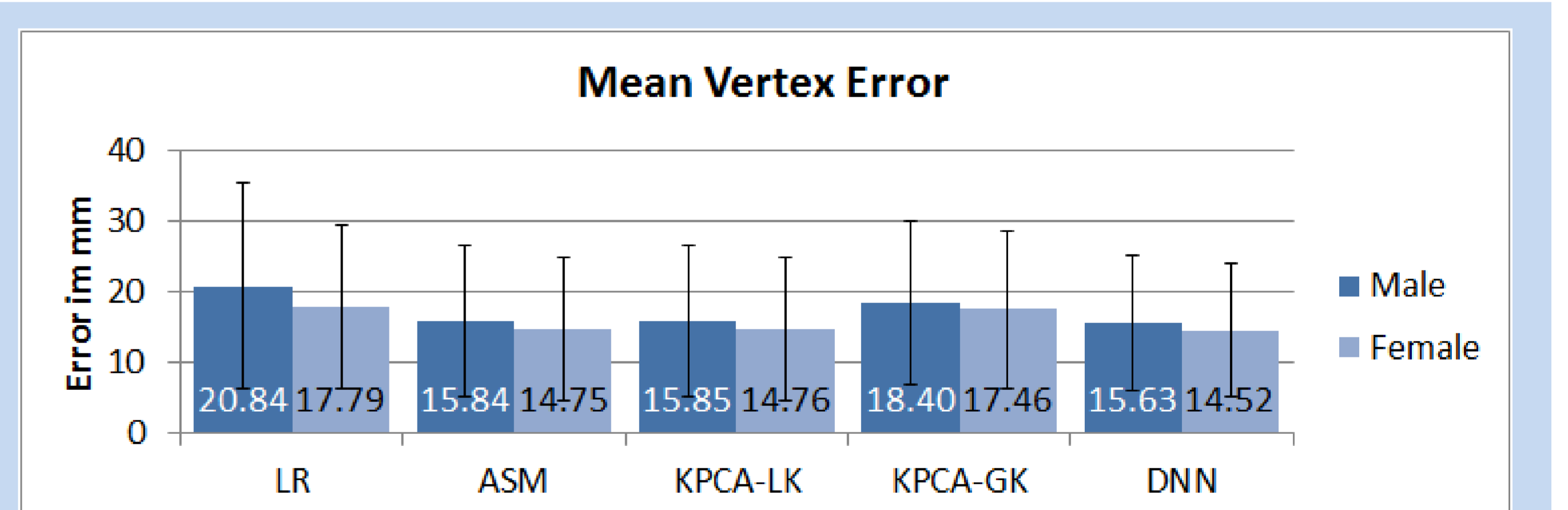


Figure 3: Mean vertex error in mm using linear regression (LR), active shape modeling (ASM), kernel PCA linear kernel (KPCA-LK), kernel PCA Gaussian kernel (KPCA-GK) and deep neural network (DNN).

Discussion and Conclusions

- A patient surface model can be reliably estimated using data-driven methods.
- The DNN method outperformed all other methods albeit slightly with a mean vertex error of 15.6 ± 9.5 mm for male and 14.5 ± 9.3 mm for female models.
- More data is needed for the DNN to outperform traditional methods by a wider margin.

Reference

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