Doctor of Engineering (EngD) in Digital Entertainment, 1st Year

Centre for Digital Entertainment

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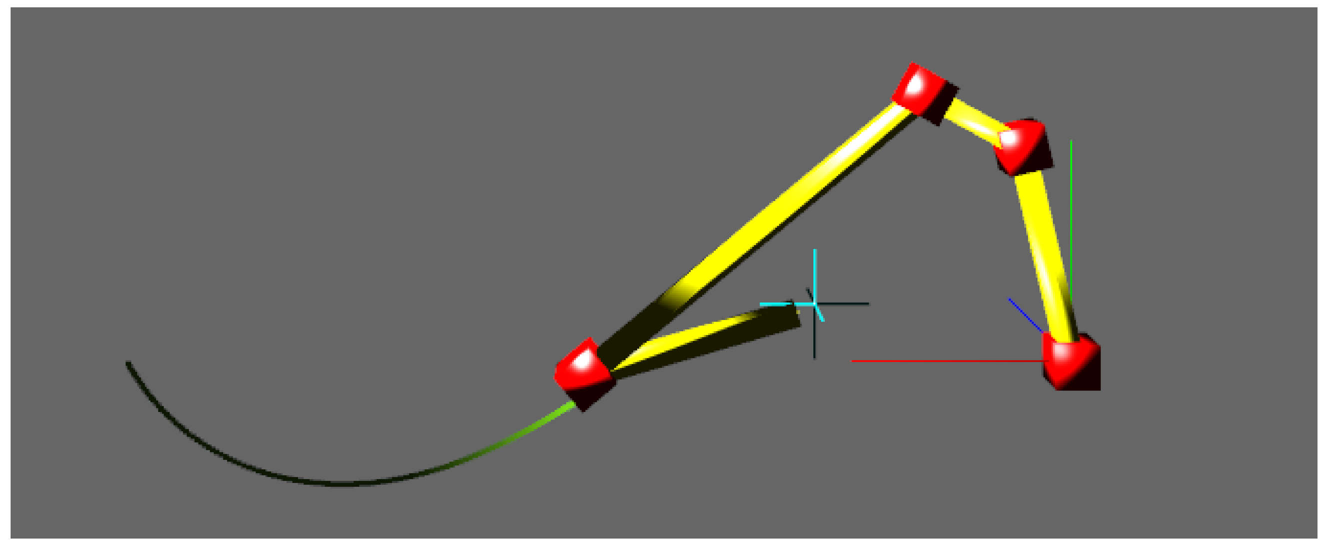
Inverse Kinematics

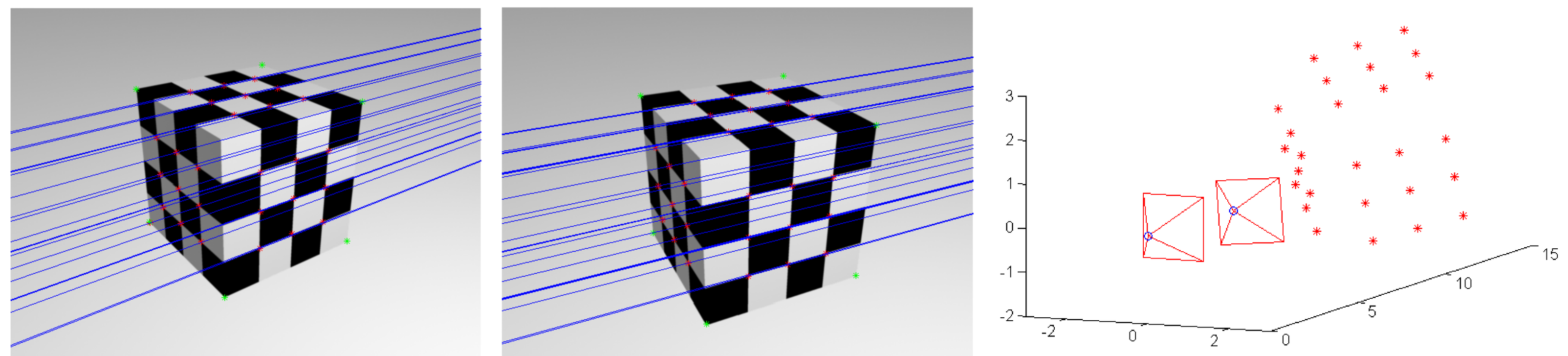


Inverse kinematics uses a known end-effector position $\mathbf{E}$ to calculate the required angles $\boldsymbol{\theta}$ between the parts which ensure that the object reaches the desired target position, such that

$$\mathbf{E} = f(\boldsymbol{\theta}) \rightarrow \boldsymbol{\theta} = f^{-1}(\mathbf{E})$$
$$\partial \mathbf{E} \approx J(\boldsymbol{\theta})\partial\boldsymbol{\theta} \rightarrow \partial\boldsymbol{\theta} \approx J^{-1}(\partial\mathbf{E}),$$

where f is the forward kinematics solver, J is the Jacobian matrix, and $J^{+} = (J^T J)^{-1} J^T$ is the pseudoinverse of J.

3D Reconstruction



A calibration cube is used to calibrate a pair of stereo cameras. The intrinsic matrix $\mathbf{K}$ and external parameters $\mathbf{R}$ and $\mathbf{t}$ can be recovered through decomposition of the projection matrices $\mathbf{P}$, where

$$\mathbf{u} = \mathbf{P}\mathbf{X} = \mathbf{K}[\mathbf{R}|\mathbf{t}]\mathbf{X}$$

The fundamental matrix $\mathbf{F}$ encompasses the intrinsic geometry between two views of a scene and defines the epipolar constraint

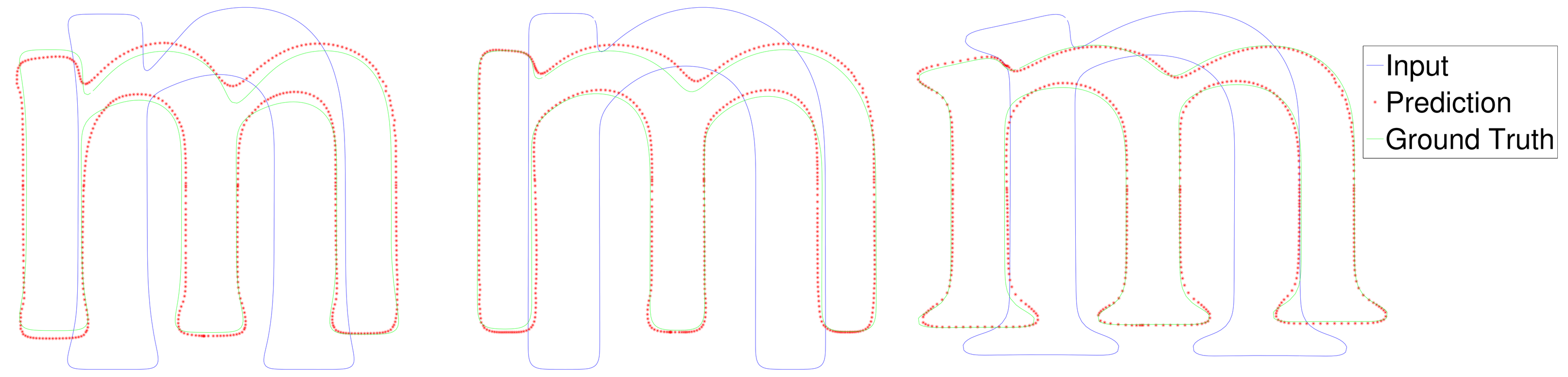
$$\mathbf{u'}^T\mathbf{F}\mathbf{u} = 0$$

We can compute epipolar lines in both views, and points which lie on epipolar lines are constrained to intersect at a point in 3D space.

References

[1] M. Alexa, D. Cohen-Or, and D. Levin. As-rigid-as-possible shape interpolation. In *Proc. of the 27th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '00, pages 157–164, NY, USA, 2000.

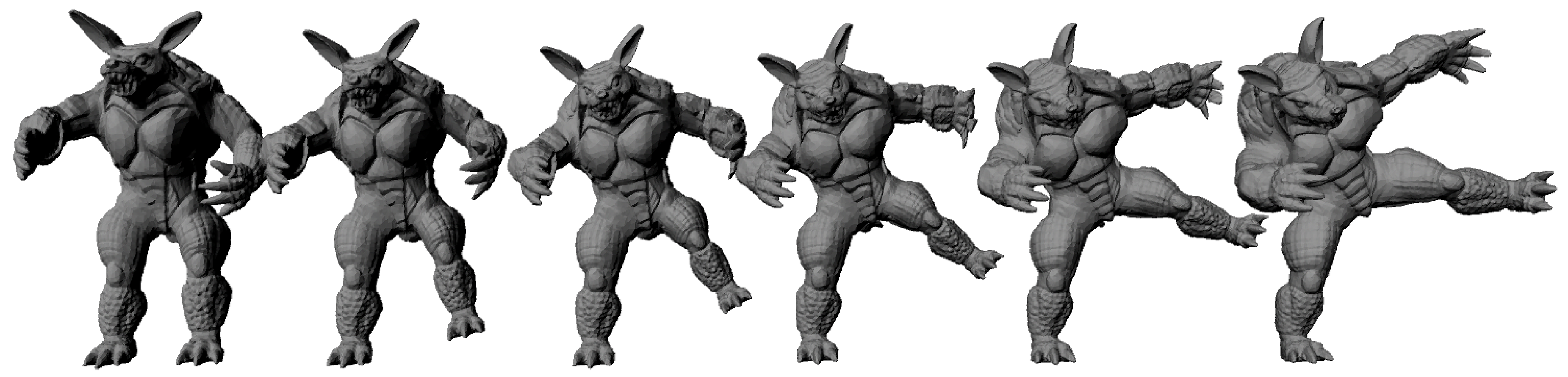
Gaussian Processes



A Gaussian process is a random process, that can be considered as an infinite-dimensional generalisation of the multivariate Gaussian distribution. The main assumption of Gaussian process modelling is that our data can be represented as a sample from a multivariate normal distribution. Each time a Gaussian process is used to model some data, a kernel has to be chosen, and its parameters tuned to maximise the likelihood.

Even with very few training examples, the Gaussian process model gives a reasonable prediction of the shape of a font. The best results were achieved using an exponential kernel with optimised length scale and variance hyperparameters.

Shape Interpolation



Alexa *et al.* [1] introduced a transformation-based interpolation technique that aims to preserve the structure of the parts that are only translated or rotated between the two meshes. For each triangle, the transformation $\mathbf{A}$ is split into rotation and translation/shearing, both of which are interpolated linearly. The corresponding smooth transformation is estimated by minimising the error in Frobenius norm:

$$E_{V(t)} = \sum_{\Delta \in \mathcal{T}} ||\mathbf{A}_T(t) - \mathbf{B}_T(t)||_F^2,$$

where $V(t)$ are the intermediate positions of vertices, $\mathbf{A}$ is the ideal mapping, and $\mathbf{B}$ is the actual affine transformation.

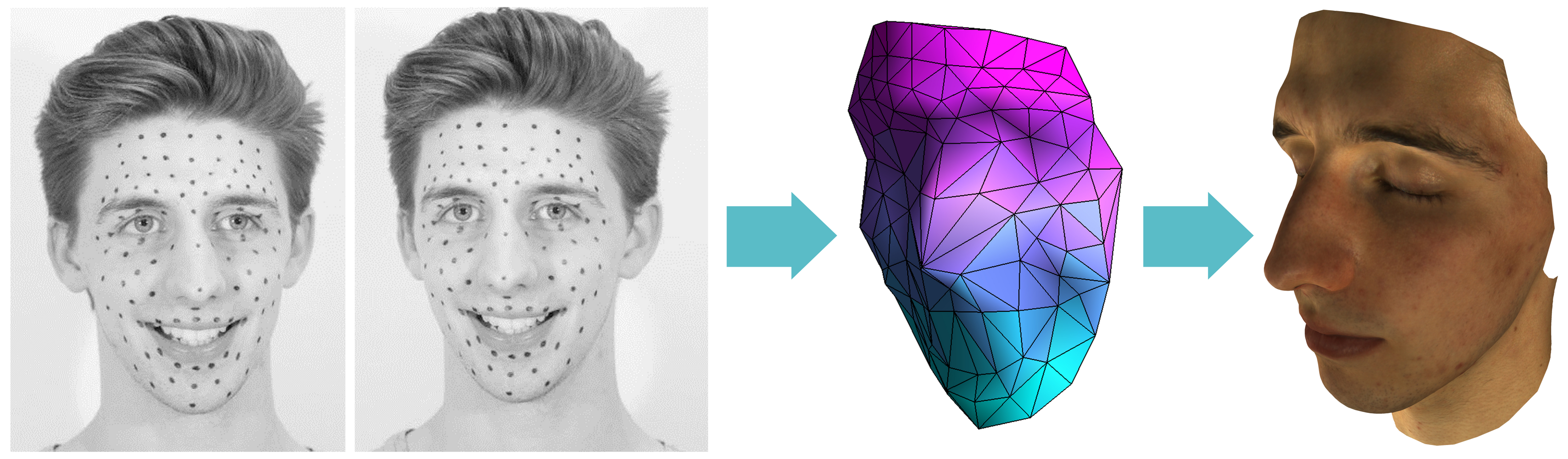
Future Research

The students undertake an individual three-month summer project in a chosen research area before starting the industrial placement.

SIFT Features

Being able to detect features in an image that are invariant to scale, rotation, translation and changes in illumination has many applications, such as image stitching and 3D reconstruction. SIFT features achieve scale invariance through extrema detection in a difference of Gaussians pyramid built from the image, while the rotation dealt with an orientation assignment based on local image properties.

Performance-driven Facial Animation



A facial performance is captured using calibrated stereo cameras and tracking markers on the face. The marker positions produce a sparse 3D point cloud, which is in turn used to drive a high-resolution mesh. A new face $\mathbf{x}^*$ can be computed from the 'neutral-face' plus a weighted combination of blend-shape faces $\{\mathbf{x}_i\}_{i=1}^N$, where the required weights $\mathbf{w} = \{w_1 ... w_N\}$ are found through an optimisation procedure

$$\mathbf{x}^* = \sum_{i=1}^{N} w_i \mathbf{x}_i$$
$$\mathbf{w} = \arg\min_{\mathbf{w}} ||\mathbf{x}^* - \sum_{i=1}^{N} w_i \mathbf{x}_i||^2$$

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