Weak Multi-View Supervision
For Surface Mapping Estimation

*Nishant Rai[1,2], *Aidas Liaudanskas[1], Srinivas Rao[1], Rodrigo Ortiz Cayon[1], Matteo Munaro[1], Stefan Holzer[1]
[1] Fyusion Inc [2] Stanford University

Introduction

Shape and structure estimation from images is a challenging task dealing with variance in shapes, perspectives, and underlying geometry.

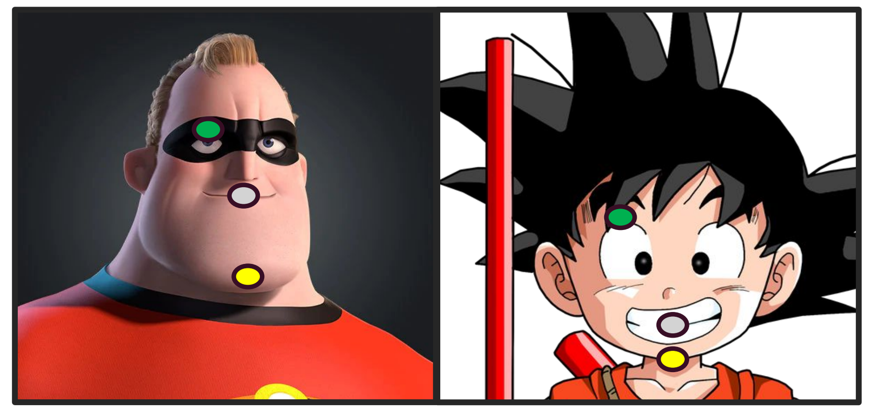
Earlier approaches have seen success using dense supervision.

We introduce a **weakly supervised multi-view approach**, along with **richly annotated datasets,** which allow us to train and evaluate comparable works.

Examples of multiple view samples from different categories in our dataset. We provide three categories: Faces, Planes, and Cars, along with additional annotations.

Motivation

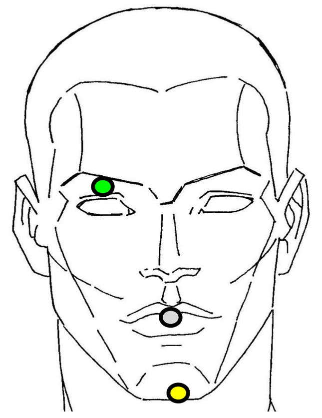
We look at the task of **surface mapping prediction from 2D images** which has traditionally been tackled using **heavy annotations** to train models.



Dense Correspondence (left): Example of correspondence of semantic points across two different facial images. Dense correspondence refers to inferring this association for all points. We utilize a top-down map (below) which serves as a universal representation of such point mapping to their respective semantic locations.

Data labelling for such a task takes a long time and makes extending to new classes very expensive.

We propose a weakly supervised approach which learns to predict both the underlying geometry and surface mapping without using dense data.



Top-Down Map: Used to define a universal reference point to map points on a surface

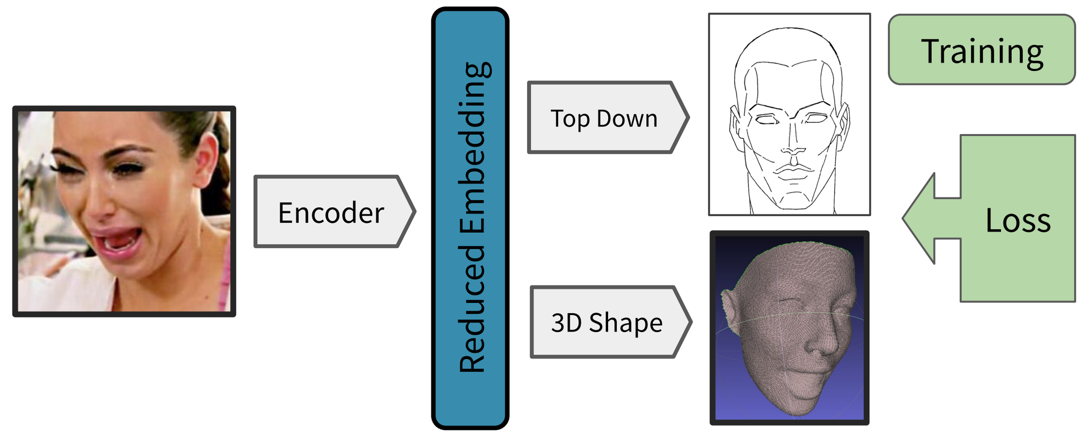
Our task is defined as **Input:** 2D Image, **Predict:** Surface Mapping, 3D shape.

Approach

Instead of using ground truth label for supervision, we use **reprojection** and **multiview consistency.**

We use camera pose **(known)**, surface mapping **(predicted)** and 3D shape **(predicted)** to compute these losses.

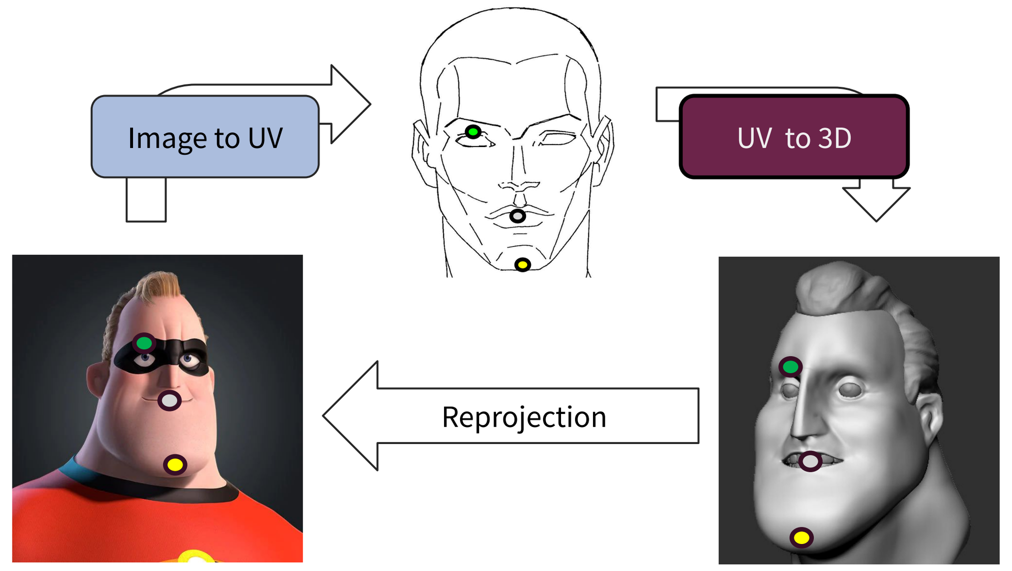
Overall Model (right): Our approach takes an image as input and uses two heads to predict the top down prediction (UV) and 3D shape for the instance. We then use these predictions to compute our loss which is needed to train the model.



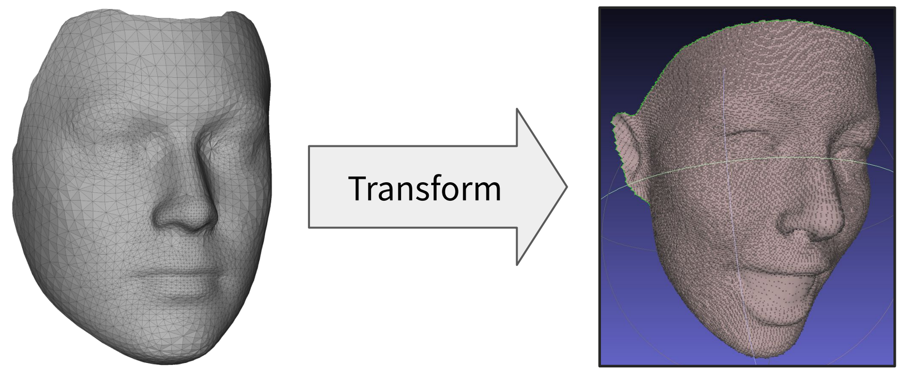
Modules

Although we use weak supervision during training, we require no additional information during inference, just a 2D image.

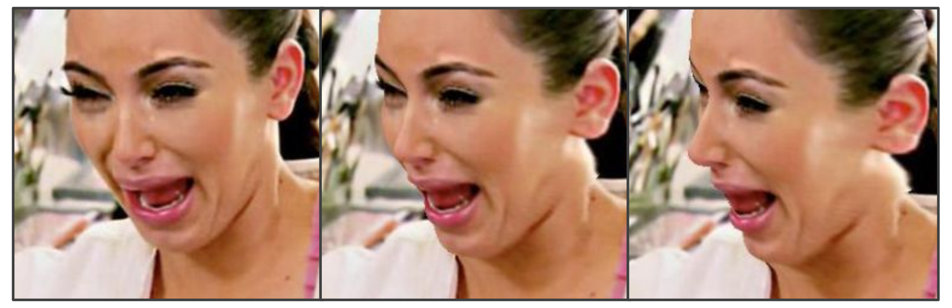
Our approach consists of three major components described below:



Reprojection Cycle: We utilize reprojection as the supervision signal.



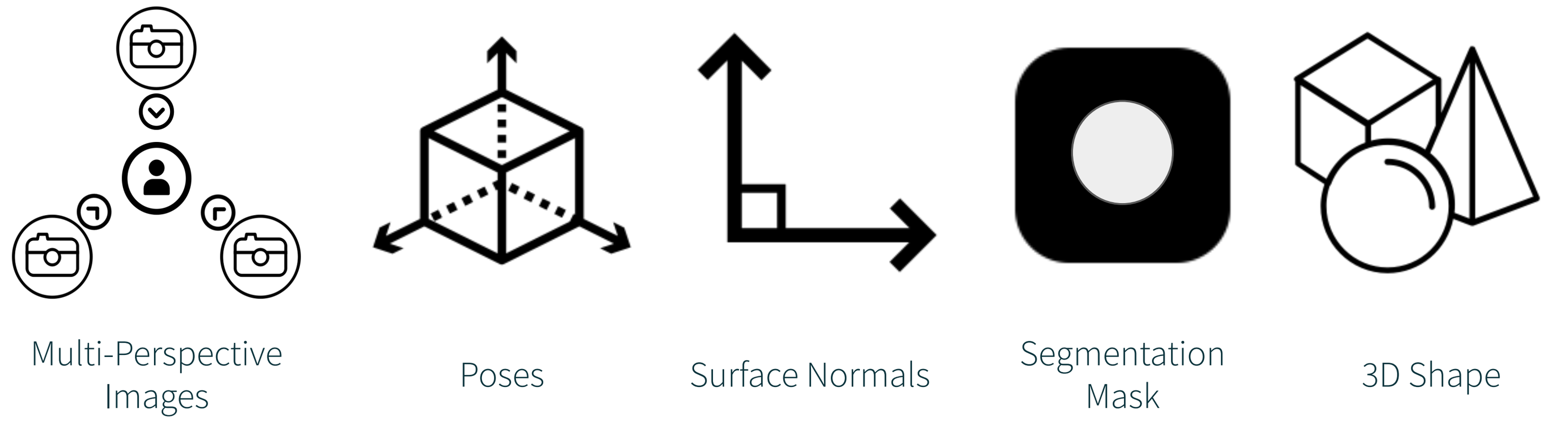
3D Shape Deformation: To handle variance in the underlying shape, we model deformations on top of a category average mesh.



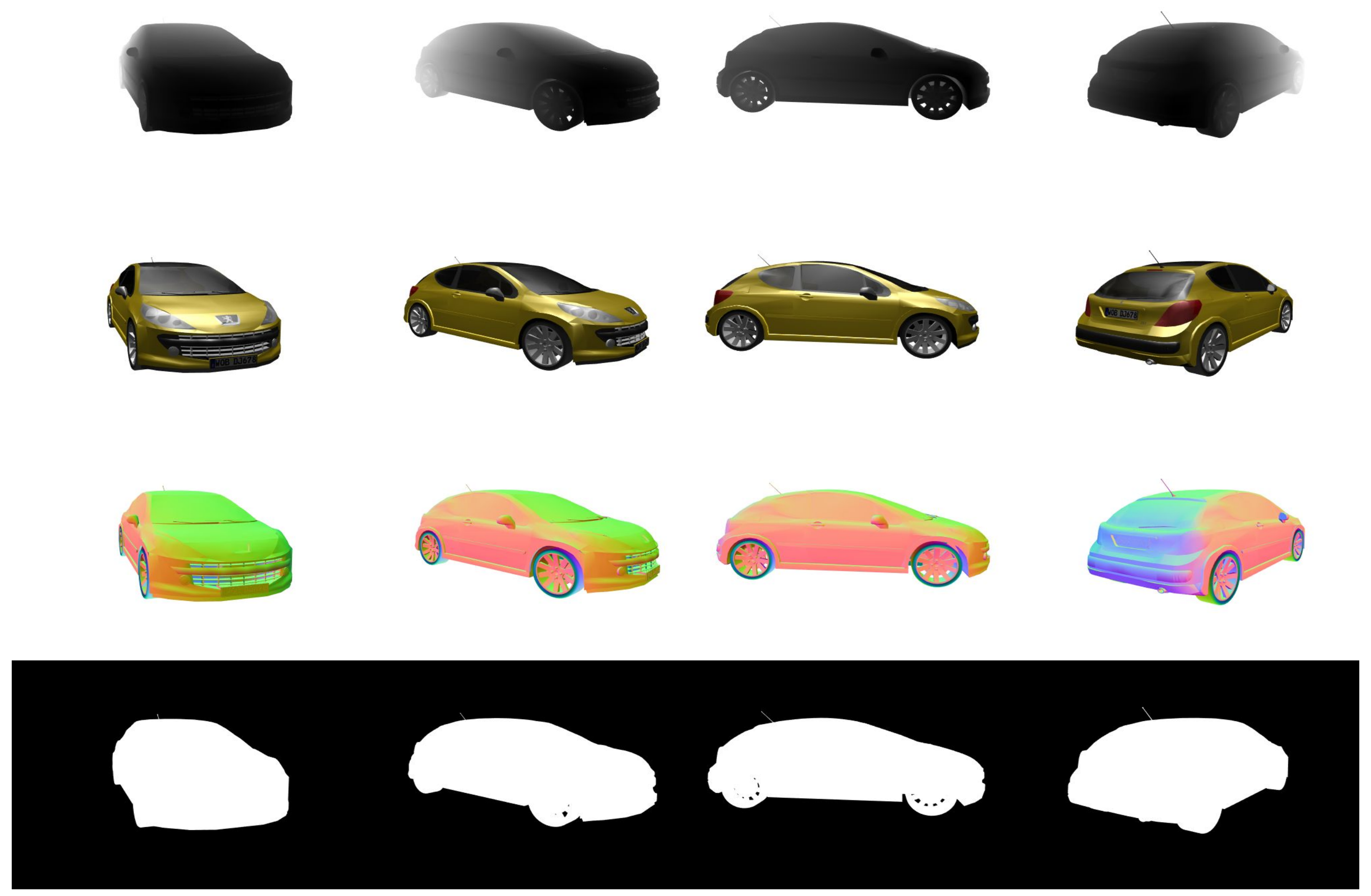
Multi View Info: We utilize predictions across multiple views and utilize inter-view reprojection to enforce consistency.

Dataset

Given the lack of datasets providing dense annotations for such tasks, we release our datasets with numerous annotations allowing training as well as evaluations.



We hope these datasets encourage research by allowing better training and evaluation of similar approaches in the future.



Our datasets contain numerous annotations for each category. Along with multi-perspective images, we also provide surface normals, segmentation masks, camera poses and 3D shapes.

Experiments

We evaluate our approach based on surface mapping and shape prediction.

UV-Pck: Evaluates the surface mapping quality; higher is better.

PosMap-Pck: Evaluates the 3D shape prediction quality; higher is better.

We also analyze how our deformed 3D shape helps vs using a fixed 3D shape.

Deformed 3D shapes **improve surface mapping quality.**

Experiments here are performed on the **multi-view face dataset** we release.

Approach	UV-Pck@ 0.01	0.03	0.1	AUC
Single-view Reprojection with Fixed Mesh	5.3	32.2	90.6	94.0
Multi-view Reprojection with Fixed Mesh	**5.8**	**34.0**	**90.8**	**94.2**
Deformed Single-view Reprojection	**13.5**	57.8	96.0	95.7
Deformed Multi-view Reprojection	13.4	**58.4**	**96.2**	**95.9**

Benefits of using multi-view training as opposed to single-view. We notice improved UV mapping quality when using deformed 3D shapes vs fixed shape.

Approach	UV-Pck@ 0.03	0.1	PosMap-Pck@ 0.03	0.1
CSM*	32.2	90.6	71.7	**98.6**
Our Approach	**58.4**	**96.2**	**72.7**	**98.6**
Fully Supervised	94.9	99.5	82.0	99.8

Our approach vs the closest weakly supervised approach (CSM - Kulkarni et al.) for this task. We notice a boost in surface mapping quality through our approach.

Future Applications

Our approach looks at simultaneous predictions of surface mapping and 3D shapes using weak supervision allowing for quick extension to new categories.

We also release datasets of Cars, Faces and Planes with rich annotations for such tasks, and hope it encourages research in this direction.

Dataset and code available on Github!

Paper: https://arxiv.org/abs/2105.01388
Github: https://github.com/Fyusion/WMVS