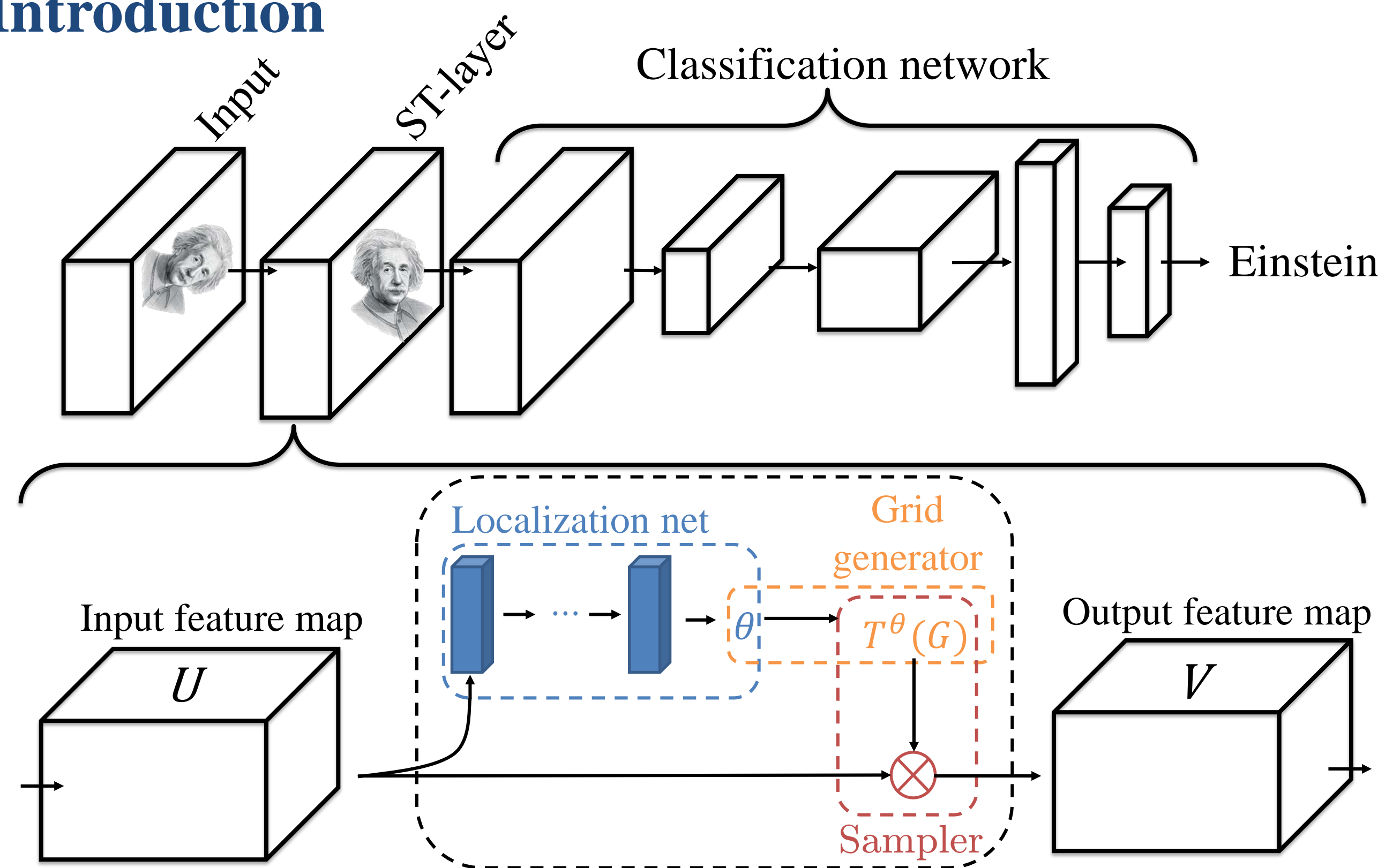


1. Introduction



Spatial Transformer layers^[1] (ST-layer) allow neural networks to be *invariant* to large spatial transformation by learning input-dependent transformations.

Problem: Current implementations support transformations that are either too restrictive e.g. affine or homographic maps, and/or destructive maps, such as thin plate splines (TPS). These kind of transformation often leads to unstable optimization of networks.

2. Method - CPAB transformations

Our solution: Incorporate differentiable flexible diffeomorphisms (namely, invertible differentiable transformations with a differentiable inverse) in ST-networks

CPAB transformations^[2-3]

1. Divide image domain into **Piecewise** tessellation
2. Equip each cell with an **Affine** velocity field
3. Enforce constrains to make **Continues** velocity field v^θ
4. **Based** on v^θ , solve an integral equation (numerically)

$$\phi^\theta(x; 1) = x + \int_0^1 v^\theta(\phi^\theta(x; \tau)) d\tau$$

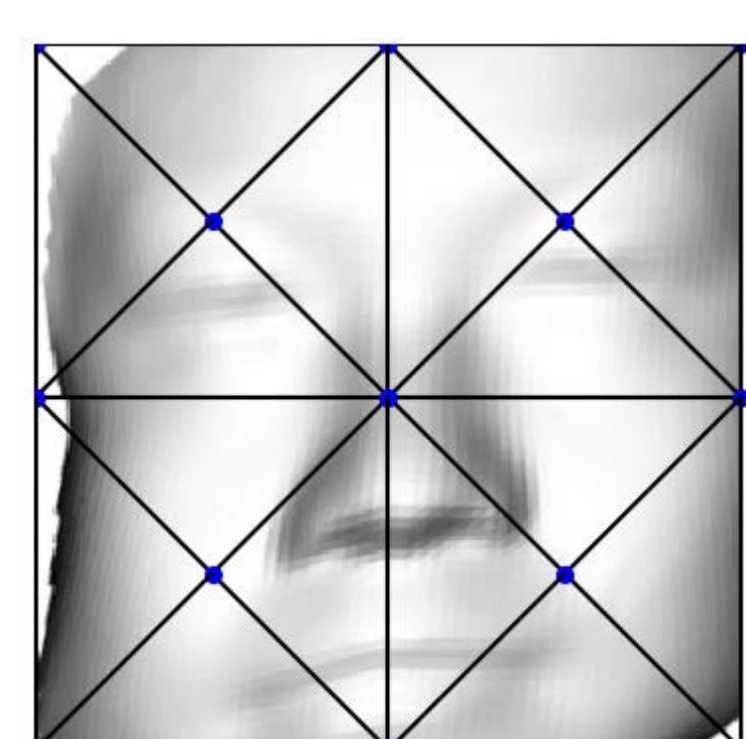
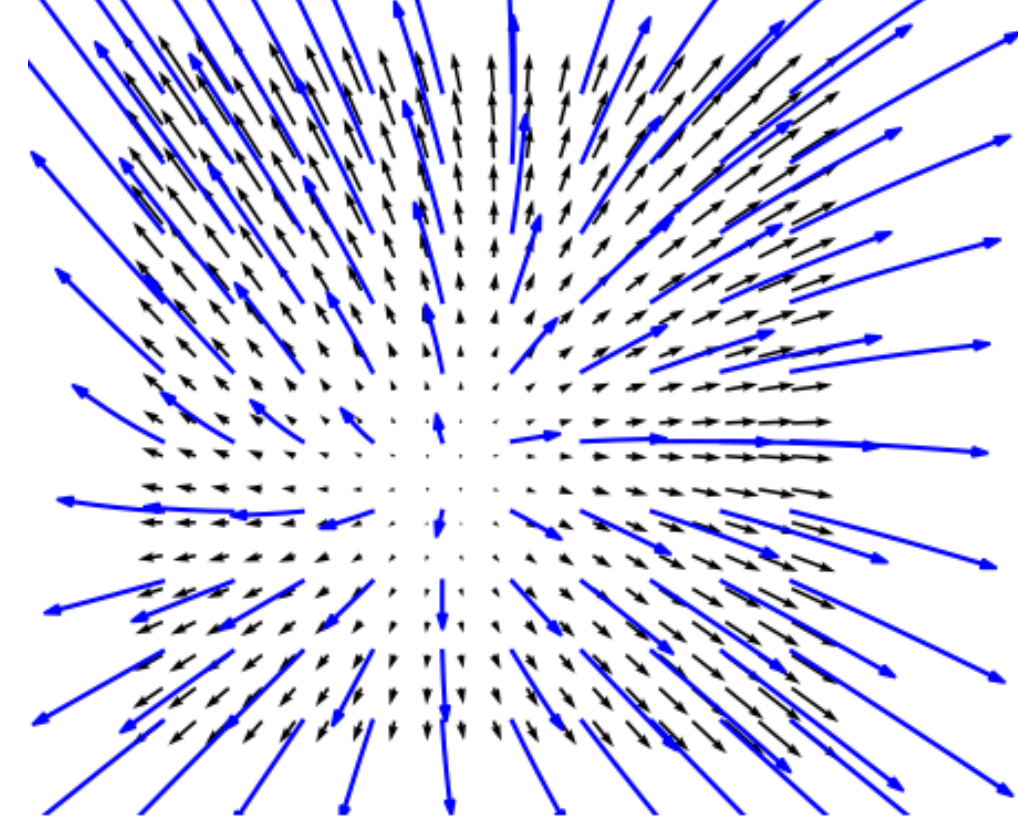
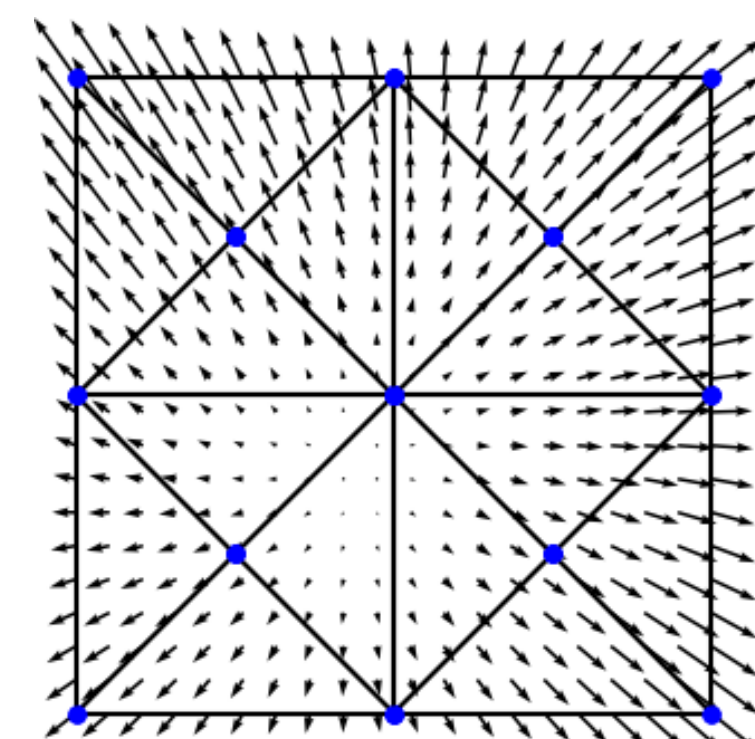
We have implemented an efficient algorithm for solving the integral in Tensorflow+CUDA.

Since the velocity field v^θ is Lipschitz continuous, our mapping $T^\theta(x) = \phi^\theta(x; 1)$ is a diffeomorphism.

Continues piecewise affine v^θ

Trajectories

Mapping



References

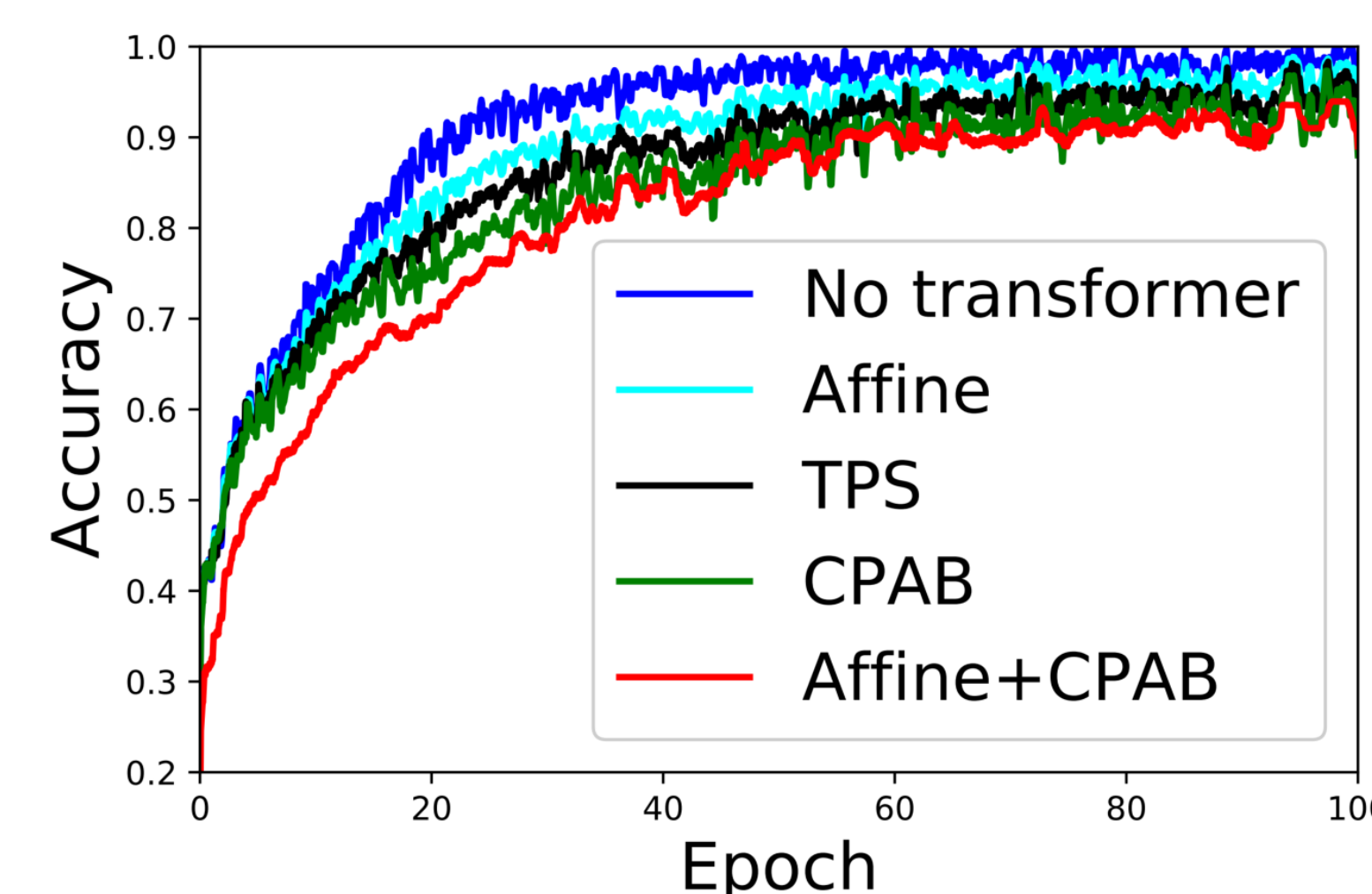
- [1] M. Jadenberg, K. Simonyan, A. Zisserman and K. Kavukcuoglu, *Spatial transformer networks*, CoRR, 2015
- [2] O. Freifeld, S. Hauberg, K. Batmanghelich, and J. W. Fisher III, *Highly-expressive spaces of well-behaved transformer: Keeping it simple*. In ICCV, 2015
- [3] O. Freifeld, S. Hauberg, K. Batmanghelich, and J. W. Fisher III, *Transformations Based on Continuous Piecewise-Affine Velocity Fields*. In IEEE-TPAMI, 2017
- [4] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, *Labeled faces in the wild: A database for studying face recognition in unconstrained environments*. Technical Report University of Massachusetts, Amherst, 2007

3. Experiments

Selection of evaluated models:

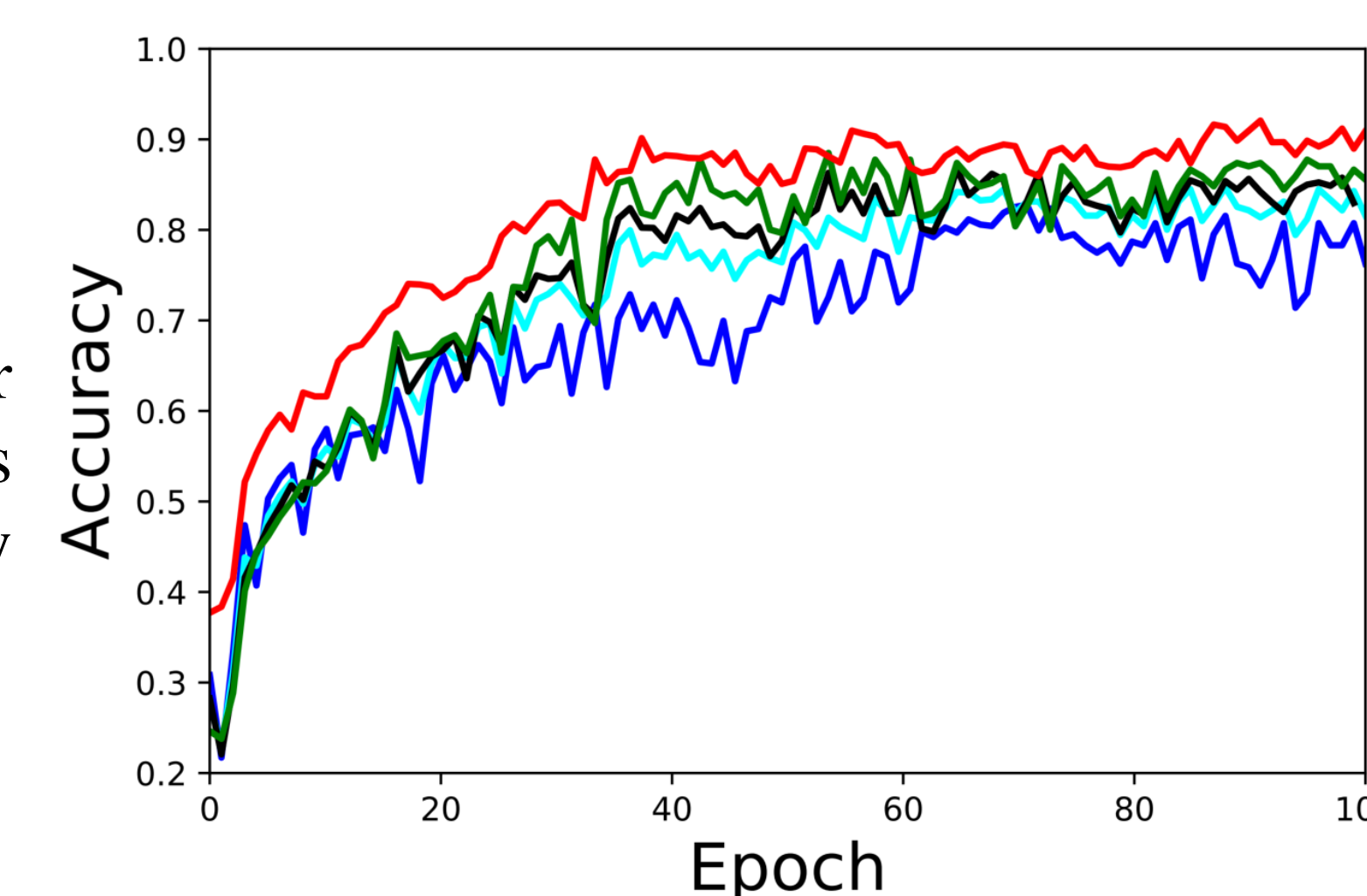
- Standard CNN
 - CNN with an ST-Affine layer
 - CNN with an ST-TPS layer
 - CNN with an ST-CPAB layer
 - CNN with an ST-Affine+CPAB layer
- On the face datasets, the ST-CPAB yields a clear performance gain.
On the other datasets, there is no clear gain (but it also doesn't hurt)

	Restricted LFW	CelebA	Unrestricted LFW
No transformer	0.788	0.712	0.893
ST-Affine	0.840	0.734	0.912
ST-TPS	0.851	0.742	0.921
ST-CPAB	0.878	0.751	0.936
ST-Affine+CPAB	0.893	0.756	0.954
State-of-the-art	0.958	0.870	0.955



← Training acc.
Validation acc. →

The proposed transformer model take more epochs to train, but eventually outperforms the others



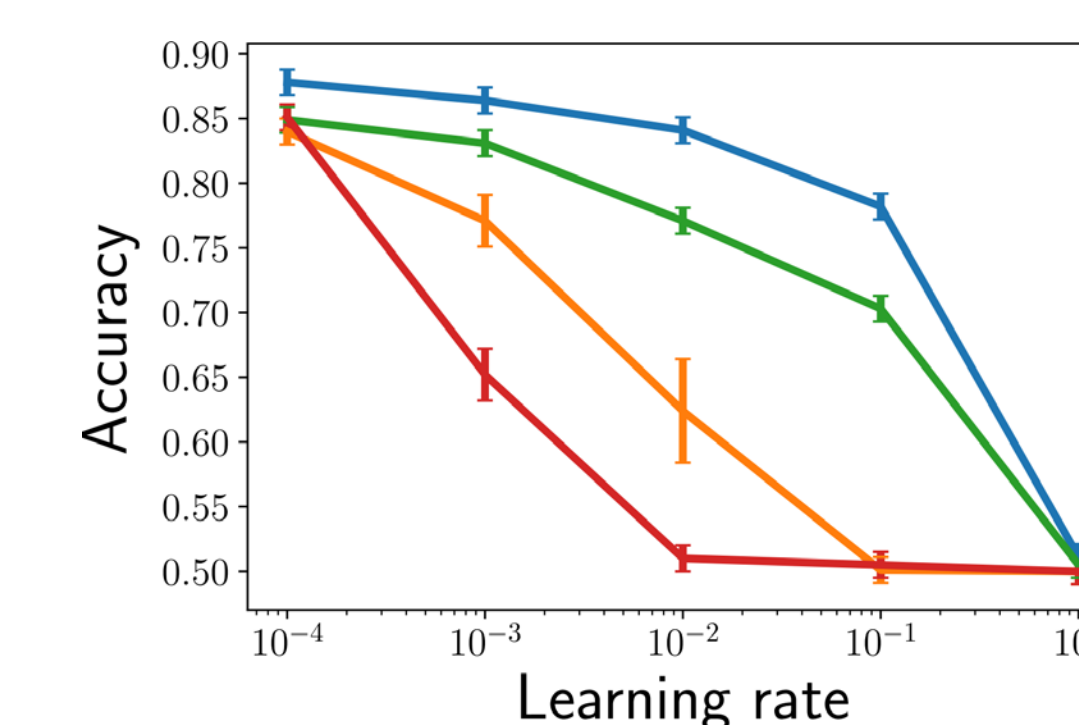
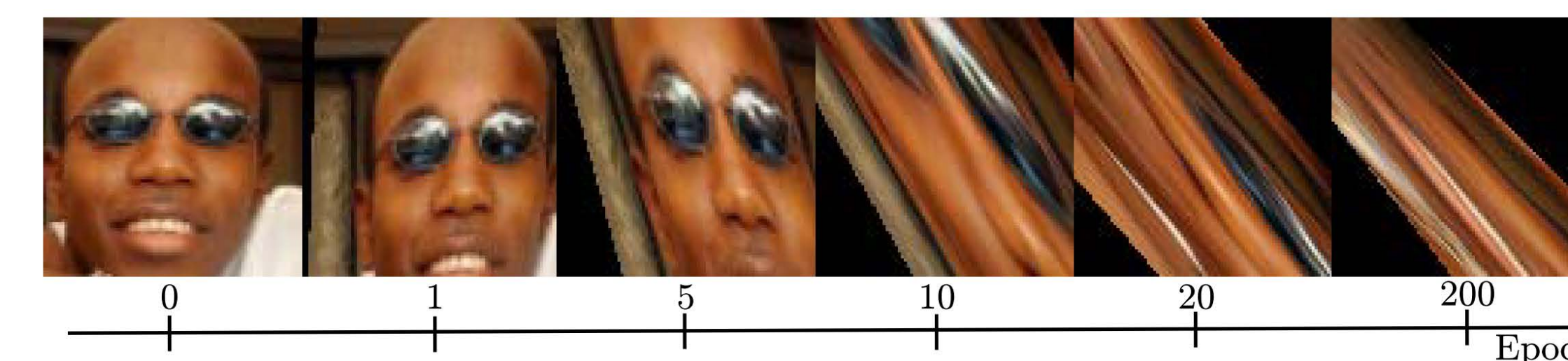
Advantages of the proposed ST-layer

- Robustness
- Flexibility
- Low dimensional

Disadvantage

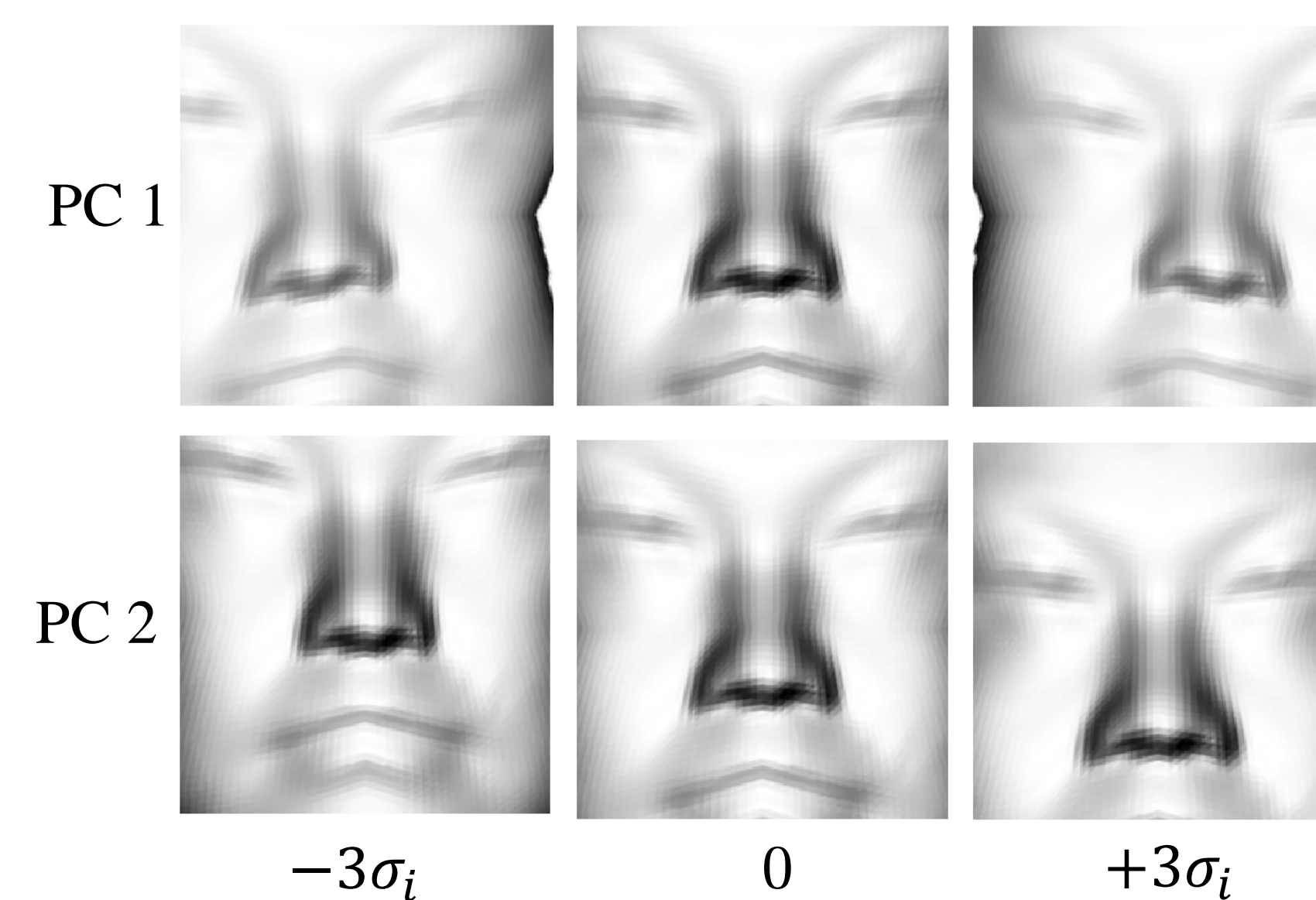
- Computational times (only during learning)

Optimizing non-invertible ST-layers is prone to instability

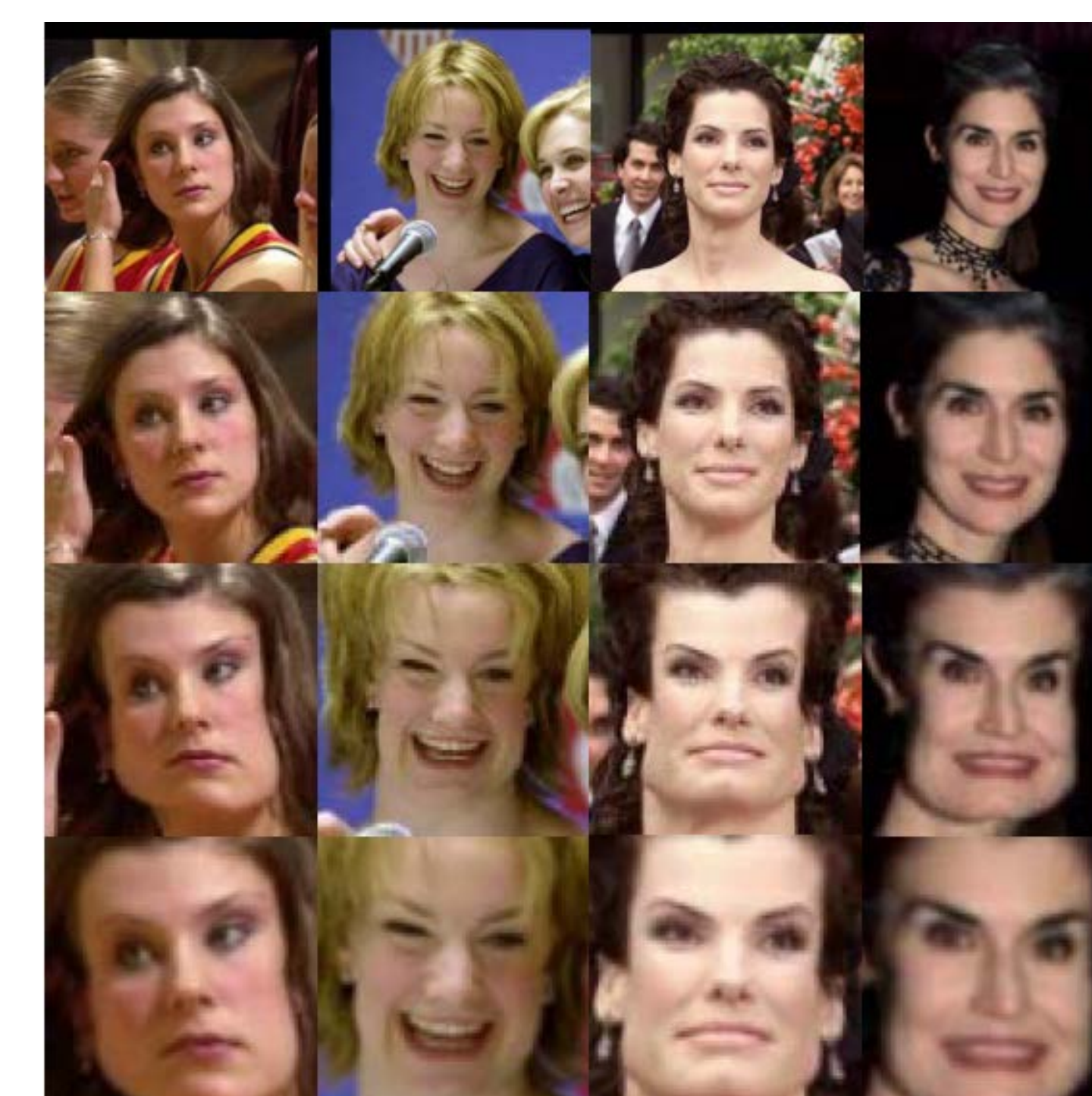


Invertible ST-layers are robust towards choice of a learning rate, compared with non-invertible ST-layers

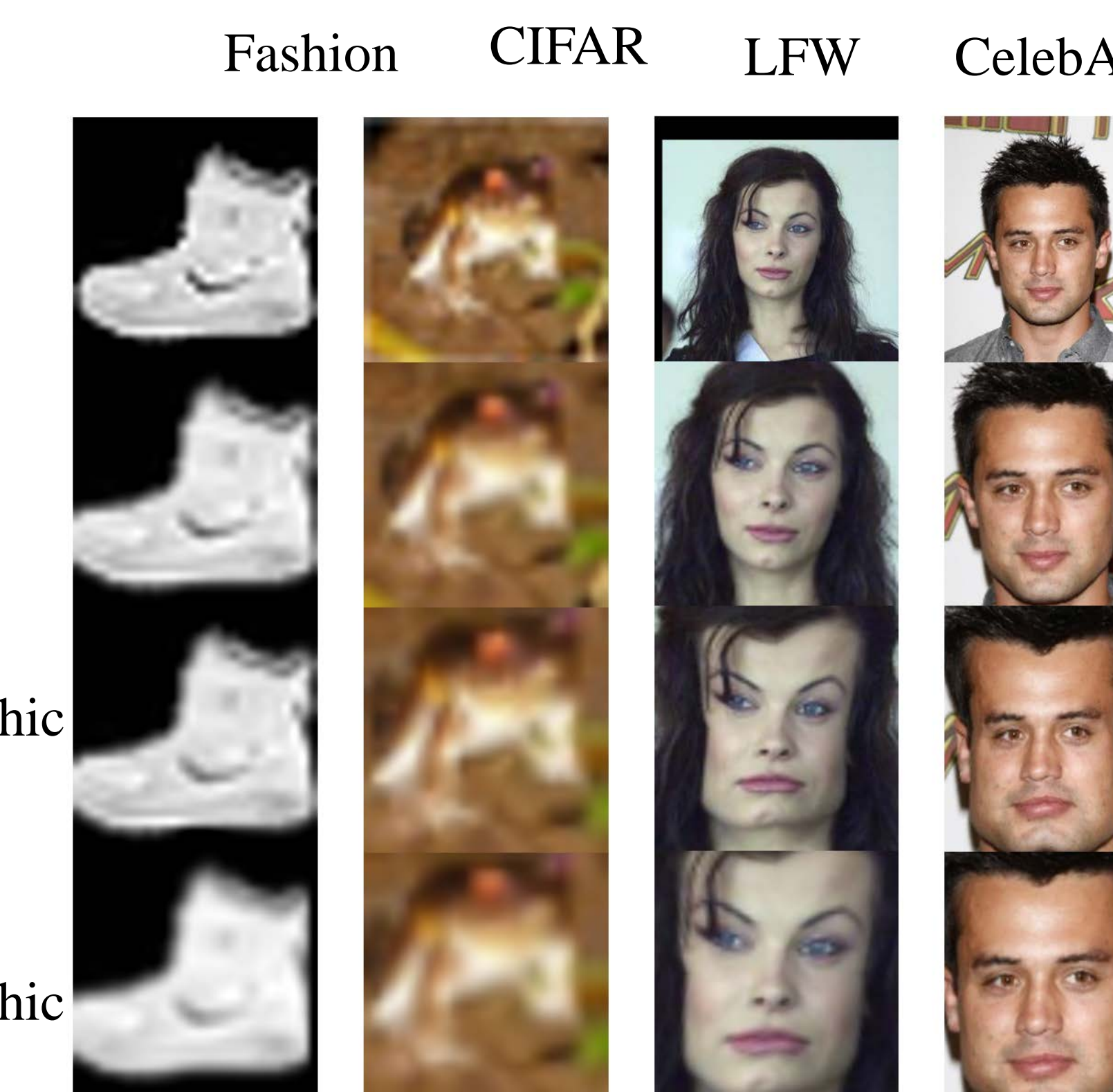
Learned facial transformations mainly zoom in on the object in focus. The two leading principal components contribute to a vertical and horizontal translation of the images.



Learning a “squarification” of the face, effectively remove the background



Transformed samples from different datasets



4. Conclusion

The proposed diffeomorphic transformation have shown:

- Good optimization properties compared to standard ST transformations
- Intuitive “squarification” transformation, given insight into possible simple data augmentation scheme
- Performance gain facial benchmark tasks
- State-of-the-art on unrestricted LFW dataset^[4]

Get the code here

<https://github.com/SkaftNicki/ddtn>