

blink · AI

Neuroscience-enhanced imaging



Bo Zhu, Co-Founder & CTO
MIT HST PhD '16, EECS M.Eng. '08, S.B. '07

Reliable low-light imaging critical to AI Computer Vision robustness

On-board video: March 2018 Uber autonomous vehicle fatal crash

COURTESY: TEMPE POLICE



Unseen pedestrian beyond headlights
Misclassified by object detection system

Our Technology

AUTOMAP: Neuroscience-inspired imaging



LETTER

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Image reconstruction by domain-transform manifold learning

Bo Zhu^{1,2,3}, Jeremiah Z. Liu⁴, Stephen F. Cauley^{1,2}, Bruce R. Rosen^{1,2} & Matthew S. Rosen^{1,2,3}

Image reconstruction is essential for imaging applications across the physical and life sciences, including optical and radar systems, magnetic resonance imaging, X-ray computed tomography, positron emission tomography, ultrasound imaging and radio astronomy^{1–3}. During image acquisition, the sensor encodes an intermediate representation of an object in the sensor domain, which is subsequently reconstructed into an image by an inversion

Inspired by the perceptual learning archetype, we describe here a data-driven unified image reconstruction approach, which we call AUTOMAP, that learns a reconstruction mapping between the sensor-domain data and image-domain output (Fig. 1a). As this mapping is trained, a low-dimensional joint manifold of the data in both domains is implicitly learned (Fig. 1b), capturing a highly expressive representation that is robust to noise and other input perturbations.

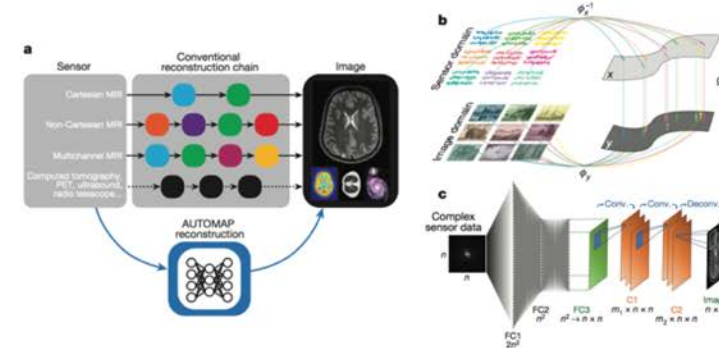
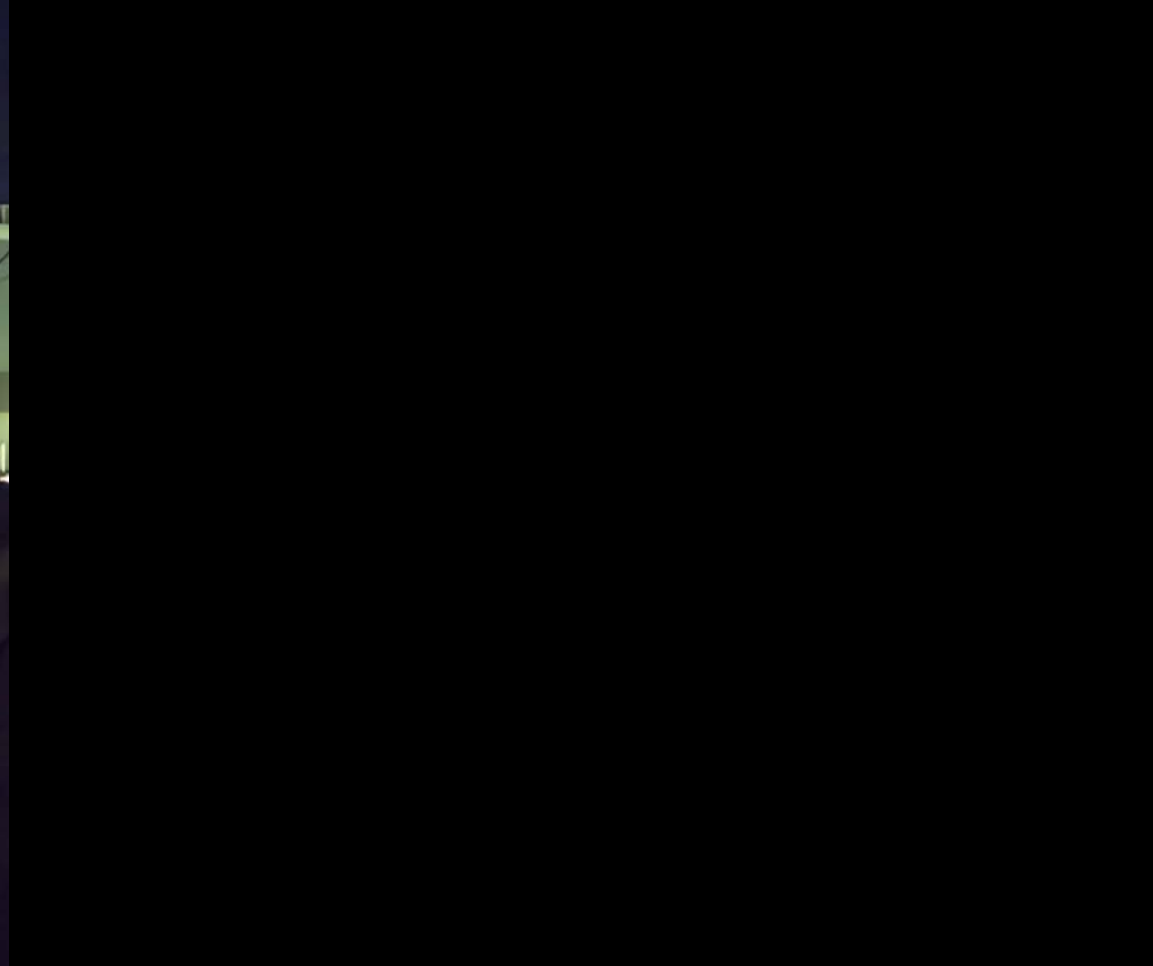


Figure 1 | Schematic representations of AUTOMAP image reconstruction. **a**, Conventional image reconstruction is implemented with sequential modular reconstruction chains composed of handcrafted signal processing stages that may include discrete transforms (for example, Fourier, Hilbert or Radon), data interpolation techniques, nonlinear optimization, and various filtering mechanisms. AUTOMAP replaces this approach with a unified image reconstruction framework that learns the reconstruction relationship between sensor and image domain without expert knowledge. **b**, A mapping between sensor domain and image

(bottom) domain pairs. The training process implicitly learns a low-dimensional joint manifold $\mathcal{X} \times \mathcal{Y}$ over which the reconstruction function $f(x) = \phi_y \circ g \circ \phi_x^{-1}(x)$ is conditioned. **c**, AUTOMAP is implemented with a deep neural network architecture composed of fully connected layers (FC1 to FC3) with hyperbolic tangent activations, followed by convolutional layers with rectifier nonlinearity activations that form a convolutional autoencoder. Our network contains m_1 and m_2 convolutional feature maps at C1 and C2 respectively. The convolution and deconvolution operations are labelled 'conv' and 'deconv', respectively. The dimensionality of the input to the network is $n \times n$. See Methods for model architecture details.



By recapitulating the cognitive process of perceptual learning - how humans learn to see – with artificial neural networks, we dramatically improve the performance of digital imaging sensors.



Samsung Galax

Premium_SmartPhone_Default.avi

BlinkAI_Solution.avi

the raw data

Avg Confide

Avg Confide

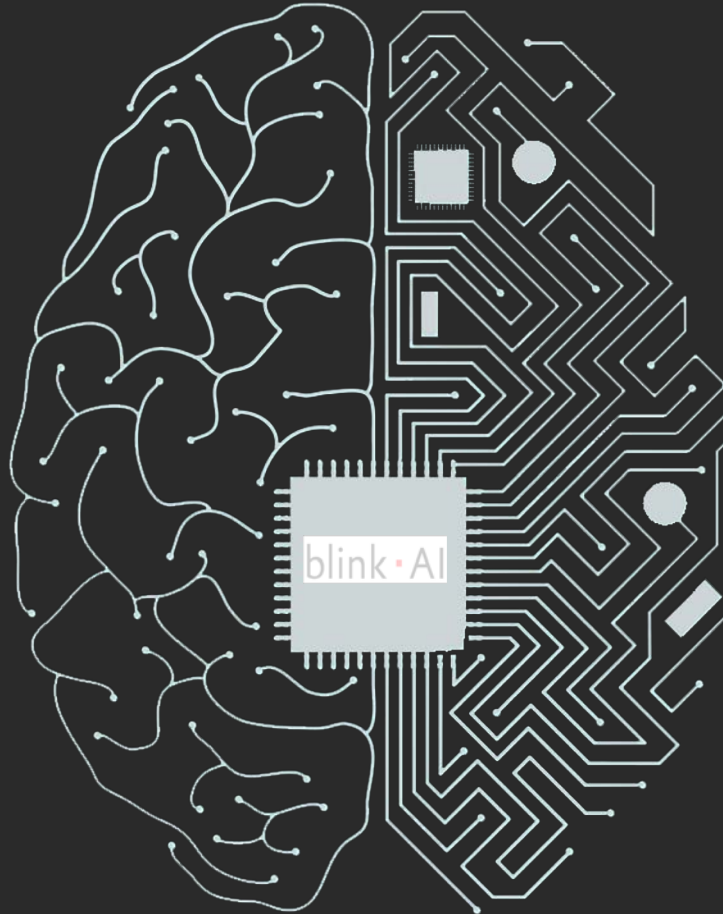
Key Value Proposition / Partnership Opportunities

Technology

Proprietary machine learning platform to maximally extract imaging data in low-signal environments

Compatibility

Computational enhancement with existing imaging hardware; boosts downstream AI high-level vision task performance



Price

Low cost computation replaces expensive large sensors and lenses

Markets

Multiple growing markets desire improved low-light imaging performance: smartphone, automotive, aerospace, security, robotics, IOT...

bo@blink.ai

www.blink.ai