Self-Supervised "Zero-Shot" SR vs Supervised SRResNet

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Context

Single-image super-resolution (SISR) traditionally relies on **supervised learning**: deep CNNs are trained on large paired LR–HR datasets (e.g., DIV2K) with known degradation models (e.g., bicubic downsampling) and evaluated on standard benchmarks (Set5, Set14, BSD100, Urban100). While this approach achieves high PSNR, it depends critically on access to representative training data and assumes the test degradation matches the training assumptions.[1],[2],[3].

In contrast, **self-supervised / zero-shot** methods such as ZSSR ("Zero-Shot" Super-Resolution) exploit a different principle: **the internal recurrence of similar patches within a single image**. Instead of training on external datasets, ZSSR trains a small CNN **at test time** using only the test image itself, creating synthetic LR–HR pairs through internal patch statistics. This enables adaptation to unknown degradations and domains where no representative training dataset exists.[2],[3],[1].

This project compares a supervised SRResNet baseline, which is trained once on external data and offers fast inference, with a ZSSR-style self-supervised CNN, which is trained per test image and requires no external data. The comparison will be conducted on standard super-resolution benchmarks to quantify differences in reconstruction quality, data dependence, and computational costs[4],[5],[6]. It is to enable students to understand both supervised and self-supervised paradigms in SISR through a focused, hands-on approach. By implementing a non-standard training protocol such as ZSSR's test-time optimization, students will develop skills in experiment design and critical analysis of method trade-offs. [3],[1].

Scientific objectives

- Implement and compare two paradigms for SISR:

- **Supervised baseline:** SRResNet-style network trained on moderate-size LR–HR datasets (General100 + BSD100).[7],[8],[1]
- **Self-supervised baseline:** ZSSR-style small CNN trained per test image using its own internal patches (zero-shot).[6],[4],[5]

- Evaluate both methods on standard SISR benchmarks (Set14, BSD100, Urban100) for ×2 or ×4 upscaling. [9],[1]
- Compare using PSNR and SSIM metrics for SR, data requirements (external training data vs none), and computational cost on the same test images.[10],[11]

Work plan

Duration: February to May (1 full day per week = approximately 12–14 working days)
Students: 2 Master-level students, with clear task allocation.

- **Phase 1** – Literature review and design (≈ eeks 1–2 of February)
- **Phase 2** – Data pipeline and baseline (≈ Weeks 3–4)
- **Phase 3** – Supervised SRResNet baseline (Student **A**, ≈ Weeks 5–8)
- **Phase 4** – ZSSR-style self-supervised model (Student **B**, ≈ Weeks 5–9)
- **Phase 5** – Joint experiments, analysis, and report (≈ Weeks 10–14, late April–May)

Contact

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Major key references

- **General SISR methods (context)**
  - *A comprehensive review of deep learning-based single image super-resolution* – overview of architectures, datasets, and metrics.[2],[3],[1]
- **Supervised SR (SRResNet context)**
  - *Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network* – use SRResNet generator as supervised baseline idea, ignore GAN.[8],[7]
- **Self-supervised / zero-shot SR (ZSSR context)**

- "Zero-Shot" Super-Resolution using Deep Internal Learning – defines zero-shot SR, internal statistics, image-specific CNN training.[12],[6],[4],[5]

- **Datasets / benchmarks context**

  - Same survey and NTIRE/benchmark discussions as above; they justify Set14, BSD100, Urban100 as standard SR test sets.[13],[9],[1],[2]

- **Metrics context**

  - *A comprehensive review of image super-resolution metrics: classical and AI-based approaches* – PSNR, SSIM definitions and discussion.[11],[10]

References

[1] A comprehensive review of deep learning-based single image super-resolution

[2] A comprehensive review of deep learning-based single image super-resolution

[3] A comprehensive review of deep learning-based single image super-resolution

[4] Zero-Shot Super-Resolution using Deep Internal Learning

[5] Zero-Shot Super-Resolution using Deep Internal Learning

[6] ZSSR: Zero-Shot Super-Resolution

[7] Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network

[8] PyTorch Tutorial to Super-Resolution

[9] Recent advances in super-resolution evaluation

[10] A comprehensive review of image super-resolution metrics: classical and AI-based approaches

[11] A comprehensive review of image super-resolution metrics: classical and AI-based approaches

[12] Zero-Shot Super-Resolution Using Deep Internal Learning

[13] NTIRE 2017 Challenge on Single Image Super-Resolution