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Enhancing License Plate Super-Resolution: A Layout-Aware and Character-Driven Approach

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Vision, Robotics and Imaging Laboratory

Summary

Problem and Motivation

- Low-resolution license plates are **common** in **real-world surveillance**.

Problem and Motivation

- Blurred and **low-quality** images **reduce** license plate recognition (LPR) **performance**

Problem and Motivation

- Need for an approach that **improves character reconstruction in low-resolution scenarios.**

Contributions

- **Novel Loss Function:** Layout and Character Oriented Focal Loss (LCOFL).

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- **Architecture improvements:** Incorporation of deformable convolutions and shared weights in attention modules.

- **Training Strategy:** A GAN-based training approach with OCR-guided discriminator for generation of more realistic and recognizable LP images.

- **Real-World Images:** Preliminary experiments with real data.

Layout and Character Oriented Focal Loss

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$$L_C = -\frac{1}{K}\sum_{k=1}^{K} w_k \log p_t(y_k^{GT}|x_k)$$

- Weighted cross-entropy to classify characters.

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- Weighted cross-entropy to classify characters.
- Penalizes misclassification from structural similarities.
- Weights are updated based on confusion matrix after each epoch.

Layout and Character Oriented Focal Loss

$$L_P = \sum_{i=1}^{K} \left[D(x_k) \cdot A(y_k^{GT}) + \cdot A(x_k) \cdot D(y_k^{GT}) \right]$$

$$\mathrm{D}(c) = \begin{cases} \beta & \text{if } c \text{ is a digit} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{A}(c) = \begin{cases} \beta & \text{if } c \text{ is a letter} \\ 0 & \text{otherwise} \end{cases}$$

- Enforces the correct positional arrangement of letters and digits in the LP layout.

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- Enforces the correct positional arrangement of letters and digits in the LP layout.
- Penalizes errors where a letter is reconstructed as a digit, or vice versa.

Layout and Character Oriented Focal Loss

$$L_S = \frac{1 - SSIM(S_i, H_i)}{2}$$

- **Guides** the network **to maintain** LP **layout and structural** details.

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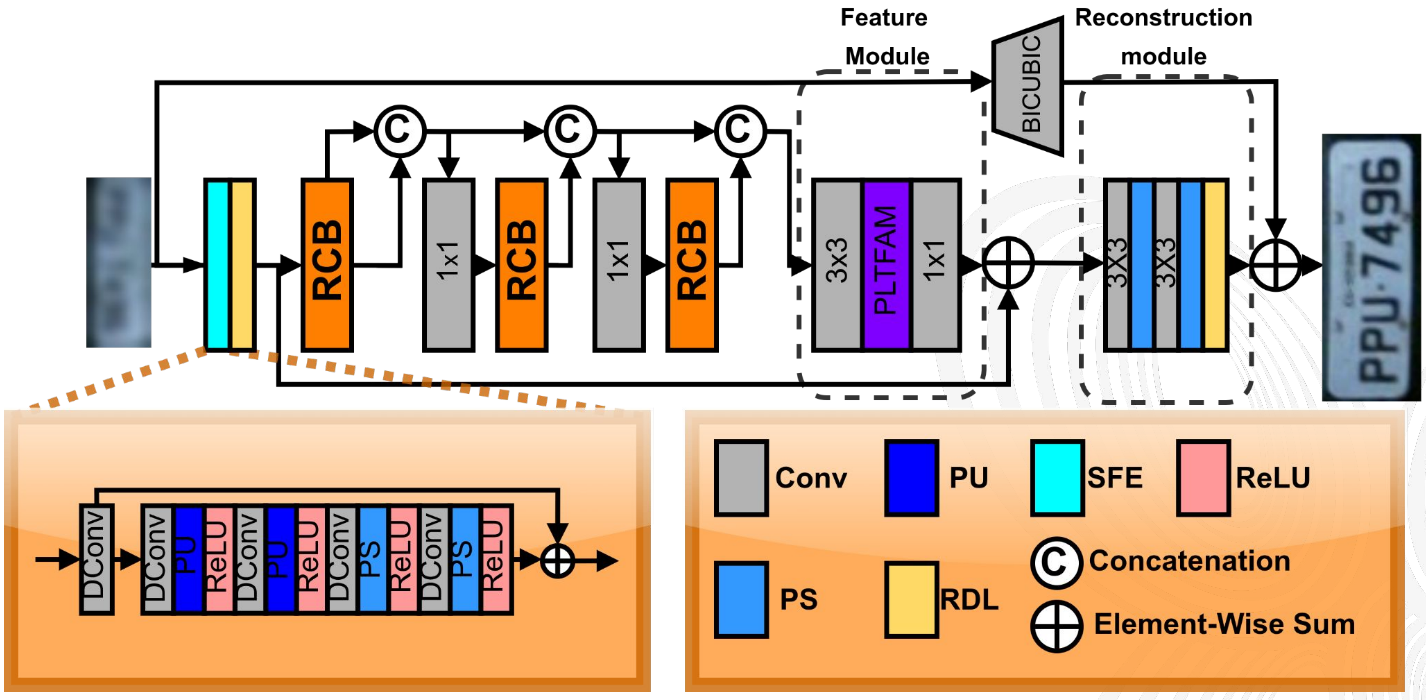
- **Guides** the network **to maintain** LP **layout and structural** details.
- **Penalizes deviations** in **texture**, **structure**, and **contrast**.

Network Architecture

Architecture



Datasets

RodoSol-ALPR[1]

- **Input Resolution (LR):** 16×48 *px*;
- **Output Resolution (HR):** 32×96 *px*.

Preliminary Real-World Images

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[1] R. Laroca, E. V. Cardoso, D. R. Lucio, V. Estevam, and D. Menotti, “**On the Cross-dataset Generalization in License Plate Recognition**” in *International Conference on Computer Vision Theory and Applications (VISAPP)*, Feb 2022, pp. 166-178.

Quantitative Results

Quantitative Results

Test Images	# Correct Characters					
	RodoSol-ALPR			***Preliminary Real-World Images***		
	All	≥ 6	≥ 5	All	≥ 6	≥ 5
HR (No SR)	98.5%	99.9%	99.9%	90.6%	98.7%	100%
LR (No SR)	**0.8%**	**4.1%**	**11.7%**	**9.9%**	**28.0%**	**56.2%**
Proposed model & baselines tested						
LR + SR (SR3 [6])	*43.1%*	*82.2%*	*82.2%*	31.7%	63.7%	80.1%
LR + SR (PLNET [5])	39.0%	59.9%	74.2%	*36.3%*	*67.2%*	*82.5%*
LR + SR (Proposed)	**49.8%**	**71.2%**	**83.3%**	**39.5%**	**70.2%**	**83.1%**

[5] Nascimento, V., Laroca, R., Lambert, J.D.A., Schwartz, W.R. and Menotti, D., "**Super-resolution of license plate images using attention modules and sub-pixel convolution layers.**" In **Computers & Graphics**, 2023, 113, pp.69-76.

[6] C. Saharia, J. Ho, W. Chan, T. Salimans, D. J. Fleet, and M. Norouzi,"**Image super-resolution via iterative refinement**," **IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)**, vol. 45, no. 4, pp. 4713–4726, 2023. Google Research.

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Qualitative Results

LR PLNET [5] SR3 [6] **PROPOSED** **HR**

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Qualitative Results

SR3 [6]

PLNET [5]

PROPOSED

HR

SR3 [6]

PLNET [5]

PROPOSED

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Ablation Study

Recognition Rates (RR) Achieved With Different Components Integrated Into The Proposed Approach

Approach	**RR**
Proposed (w/o ArchMod, GAN-style, and LCOFL)	39.0%
Proposed (w/o LCOFL)	45.9%
Proposed (w/o ArchMod and LCOFL)	47.6%
Proposed (w/o GAN-style and LCOFL)	47.7%
Proposed (w/o ArchMod and GAN-style)	48.2%
Proposed (w/o ArchMod)	49.2%
Proposed (w/o GAN-style)	49.4%
Proposed	49.8%

Final Remarks

- Our approach involved the implementation of LCOFL for character reconstruction according with the LP layout.

- LCOFL effectively mitigates confusions between structurally similar characters.

- Modifications to the archicture and training procedure led to state of the art results.

Final Remarks - Future Works

- Conduct experiments on various LP layouts.
- Complete the paired real-world LR/HR dataset and make it publicly accessible for researchers.
- Ensure the dataset supports multi-image super-resolution.

THANK YOU!

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