Supervised re-identification does not scale to large camera networks. Poor generalization properties to unseen camera conditions. Requires fine-tuning - often hundreds of image pairs.

**Contributions**

- A metric split into texture and color components.
- Color invariant deep texture learned with only intensity images.
- One-shot metric learning based on patches of a ColorChecker chart.
- Spatial variations are handled by explicitly modeling background distortions.

**Approach: One-Shot Metric Learning**

We learn a Mahalanobis metric

\[
d^2(x_i, x_j) = (x_i - x_j)^T M (x_i - x_j),
\]

where \( M \) is split into texture and color components:

\[
M = \begin{bmatrix}
I & 0 \\
0 & G
\end{bmatrix}
\]

Texture pre-trained on intensity images from multiple datasets.

Color metric learned with a single pair of ColorCheckers.

\[
M = \begin{bmatrix}
I & 0 \\
0 & G
\end{bmatrix}
\]

**Spatial Variations**

- Patches at different locations have different amounts of background pixels.

Spatial Variations are handled through a simple model.

\[
\begin{align*}
\Sigma^{T(n)} &= \Sigma^{T} + \alpha^{15} \Sigma^{+} & \alpha^{15} & = 0.08 \\
\Sigma^{T+} &= \Sigma^{T} + \alpha^{19} \Sigma^{+} & \alpha^{19} & = 0.19
\end{align*}
\]

Features extracted on a fixed grid may not correspond due to pose changes.

Define a linear patch assignment problem to accommodate pose misalignments - solved by the Hungarian algorithm.

**Experimental Results**

- Color Calibration on CCH dataset

- \( \gamma \) sensitivity

- \( \gamma \) controls relative importance of color