Latent Fingerprint Segmentation with Adaptive Total Variation Model

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Three types of Fingerprint Images

1. Rolled
2. Plain
3. Latent

Fingerprint Segmentation

Foreground (Fingerprint)

Background (Noise)
LATENT FINGERPRINT SEGMENTATION
THE CHALLENGE

Six types of Structured Noise

Signal << Noise
Fingerprint (Weak)  Structured Noise (Strong)
Segmentation features (*mean, coherence, variance*) used for rolled/plain fingerprints fail to work on latent fingerprints.
THE TOTAL VARIATION (TV) MODEL

The TV-Decomposition Problem

Split a given image $f$ into 2 layers:
1. Structural Layer (cartoon $u$)
2. Textural Layer (texture $v$)

\[ f = u + v \]

- $f$: Observed Image (Texture + Noise)
- $u$: Cartoon (Object hues and sharp edges)
- $v$: Texture (Repeated structure of small patterns)
THE TOTAL VARIATION (TV) MODEL

The TV Model

\[
\min_{u \in BV} \left\{ \int |\nabla u| \, dx + \frac{\lambda}{2} \|u - f\|_{L^2}^2 \right\}
\]

Total Variation: Measures the amount of oscillation in \( u(x) \).
Fidelity Term: How close is \( u \) from the original image \( f \)?
\( \lambda \): Tuning parameter, \( \lambda \geq 0 \).

Applications
Denoising, Deblurring, Decomposition, Inpainting…
**TV-L1 MODEL**

**MULTISCALE FEATURE SELECTION**

TV-L1 Model:

\[
\min_u \int |\nabla u| + \lambda \int |u - f| \, dx
\]

Parameter \( \lambda \) controls the scale of extracted features in \( v \).

Original Image \( f \)

- \( u \) (\( \lambda = 0.10 \))
- \( u \) (\( \lambda = 0.30 \))
- \( u \) (\( \lambda = 0.70 \))

- \( v \) (\( \lambda = 0.10 \))
- \( v \) (\( \lambda = 0.30 \))
- \( v \) (\( \lambda = 0.70 \))

- **u**: Cartoon layer
- **v**: Texture layer

*Image Source: USC*
TV MODEL FOR LATENT SEGMENTATION

THE PROBLEM

Two Problems

1. Small scale Structured Noise

- Text Letters
- Lines
- Dots & random noises

STILL LEFT

2. Boundary Signal

- u
- v
Our Proposed Model

\[ \min_u \int |\nabla u| + \int \lambda(x) |u - f| \, dx \]

TV term \hspace{2cm} Spatially Variant Fidelity term

Spatially varying fidelity \( \lambda(x) \)

Large \( \lambda(x) \) => Most textures stay in \( u \)
Small \( \lambda(x) \) => Small scale textures start to vanish
All textures disappear in \( u \)
SOLUTION TO PROPOSED MODEL

Difficulty in solving TV-based models

- The total variation norm is **NOT differentiable**.

\[
\min_u \int |\nabla u| + \int \lambda(x) |u - f| \, dx
\]

TV term

Existing numerical algorithms

1. Gradient descent.
2. Split Bregman Iteration.
3. Duality-based methods.
   - CGM dual method, Chambolle’s dual method
4. Splitting and penalty based methods.
   - Augmented Lagrangian method.
Augmented Lagrangian of ATV-L1 Model:

Adaptive TV-L1 Model (ATV-L1):

\[
\min_{x} f(x) \quad \text{subject to } c_i(x) = 0
\]

is turned into minimizing the augmented Lagrangian:

\[
L_A(x, \lambda; \mu) \triangleq f(x) - \sum_i \lambda_i c_i(x) + \frac{\mu}{2} \sum_i c_i^2(x)
\]

Algorithm 1. Augmented Lagrangian method for our proposed adaptive TV-L1 model.

1. Initialization:
   \[ u^0 = 0, \ p^0 = 0, \ v^0 = 0; \]

2. For \( k = 1, 2, \ldots, \) compute:
   \[
   (u^k, p^k, v^k) = \underset{(u, p, v)}{\arg\min} \Sigma(u, p, v, \lambda_p, \lambda_v) \quad (5)
   \]

3. Update:
   \[
   \begin{align*}
   \lambda_{p}^{k+1} &= \lambda_{p}^{k} + r_{p}(p^{k} - \nabla u^{k}) \\
   \lambda_{v}^{k+1} &= \lambda_{v}^{k+1} + r_{v}(v^{k} - u^{k})
   \end{align*}
   \]
PARAMETER ESTIMATION

\[ \min_u \int |\nabla u| + \int \lambda(x) |u - f| \, dx \]

**TV term** \hspace{2cm} **Spatially Variant Fidelity term**

**Question:** How do we choose \( \lambda(x) \)?

**Goal:** Extract fingerprint to \( v \), keep noise in \( u \).

<table>
<thead>
<tr>
<th>Region</th>
<th>Important aspect for cartoon layer ( u )</th>
<th>Ideal ( \lambda(x) )</th>
<th>Content in texture layer ( v )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fingerprint</td>
<td>Smoothness</td>
<td>Small</td>
<td>Texture extracted to ( v )</td>
</tr>
<tr>
<td>Noise</td>
<td>Fidelity</td>
<td>Large</td>
<td>Noise kept away from ( v )</td>
</tr>
</tbody>
</table>
When a region is filtered by a low-pass filter:

- **Edge/Smooth**: small decrease in local total variation (LTV).
- **Texture**: large decrease in LTV.

\[
L_\sigma(\xi) = \frac{1}{1 + (2\pi\sigma |\xi|)^4}
\]

Differential LTV Reduction Rate

- Describes the oscillatory behavior of the local texture at scale $\sigma$.
- Fingerprint regions have a sharp peak at $\sigma = 2.0$.

**Definition**

\[
\eta_\sigma = \frac{LTV(L_\sigma * f) - LTV(L_{\sigma-1} * f)}{LTV(f)}
\]

Finally we take:

\[
\lambda(x) = \kappa \cdot \frac{1}{\eta_c(x) + \epsilon}
\]

(c is chosen as 2.0)
After Decomposition by Adaptive TV-L1 Model:

- Cartoon $u$: structured noise + small scale structures.
- Texture $v$: fingerprint + small amount of noise. Noise with high variance is removed, variance feature can be used for segmentation.
Experimental Results

Experimental Data
NIST SD27 Database, 258 latent fingerprint images

Texture Layer v (\(\lambda=0.50\))
Non-adaptive TV-L1

Texture Layer v
Proposed Adaptive TV-L1
Top Left: Original Image
Top Right: λ Map
Bottom Left: Texture ν
Bottom Right: Seg Result

RESULTS
RESULTS

Top Left: Original Image
Top Right: $\lambda$ Map
Bottom Left: Texture $v$
Bottom Right: Seg Result
Adaptive TV-L1 Model

$$\min_u \int |\nabla u| + \int \lambda(x) |u - f| \, dx$$

- Decompose a latent fingerprint image into two layers and effectively locate the region-of-interest (ROI).
- Fidelity weight coefficient $\lambda(x)$ is automatically adapted to the background noise level.

Future Work

- Performance benchmarking for segmentation.
- Further exploit the ridge orientation information of fingerprints. Isotropic TV Model $\rightarrow$ Anisotropic TV Model.
ACKNOWLEDGEMENTS
QUESTIONS?
TV-L1 MODEL
MULTISCALE FEATURE SELECTION

λ increases
Smaller features appear in v

Original Image f

u (λ=0.10)  u (λ=0.30)  u (λ=0.70)

v (λ=0.10)  v (λ=0.30)  v (λ=0.70)

u: Cartoon layer
v: Texture layer
TV-L1 MODEL
MULTISCALE FEATURE SELECTION

TV-L1 Model:
\[
\min_u \int |\nabla u| + \lambda \int |u - f| \, dx
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Parameter \( \lambda \) controls the scale of extracted features in \( v \).

Original Image \( f \)

Small \( \lambda \)  

Large \( \lambda \)

Cartoon \( u_i \)

Texture \( v_i = f - u_i \)

Feature \( u_{i+1} - u_i \)