Entire Reflective Object Surface Structure Understanding

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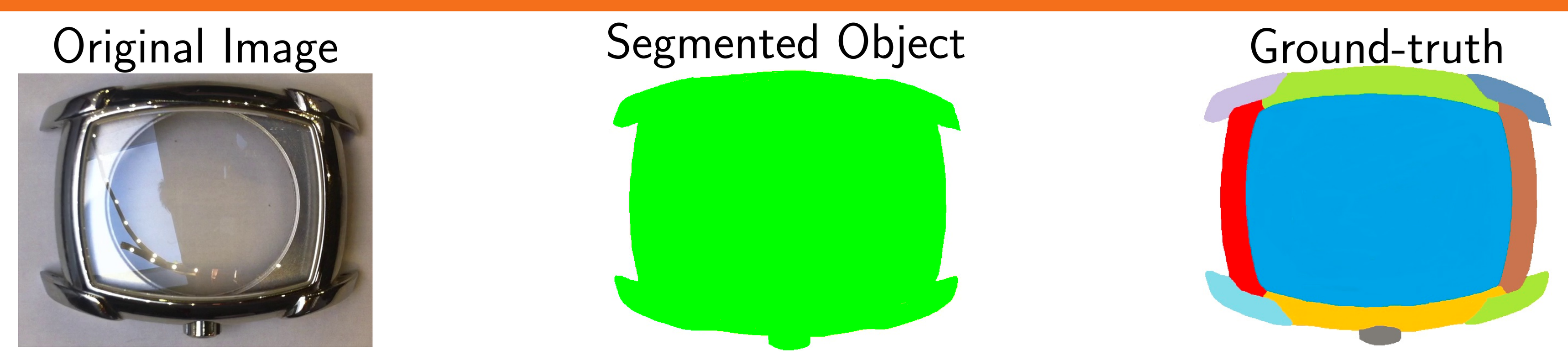
Abstract

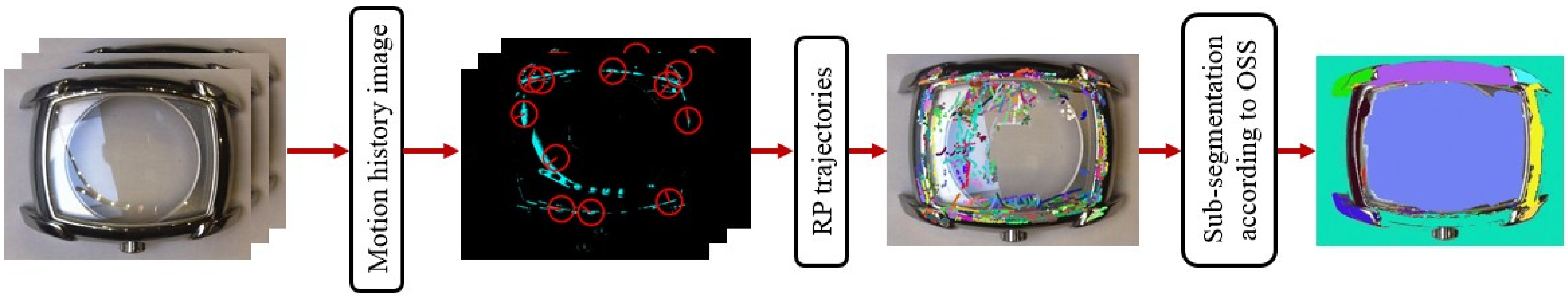
Reflection from reflective surface has been a long-standing problem for object recognition, it brings negative effects on objects color, texture and structural information. Because of that, it is not a trivial task to recognize the surface structure affected by the reflection, especially when the object is entirely reflective. Most of the time, reflection is considered as noise. In this paper, we propose a novel method for entire reflective object sub-segmentation by transforming the reflection motion into object surface label. Instead of considering the reflection as noise, our approach takes reflection as an advantage for understanding the surface structure of the entire reflective objects. The experimental results on specular and transparent objects show that the surface structures of the reflective objects can be revealed and the segmentation based on the surface structure outperforms the approaches in literature.

Motivation

1. The surface structure graph of an object is a highly representative feature.
2. Reflection ruins the features as color, texture, and contour.
3. Take advantage of reflection instead of removing it.
4. Segment elementary continuous surfaces to obtain graph representation.



Reflective Object sub-segmentation



Reflection Motion Feature Extraction

Motion History Image:

$$H_\tau(x,y,t)=\begin{cases}\tau & \text{if} \quad \Psi_\tau(x,y,t)=1\\ max(0, H_\tau(x,y,t-1)-\delta) & \text{if} \quad \Psi_\tau(x,y,t)=0\end{cases}$$

$\Psi_\tau(x,y,t)$ = motion in current frame

τ = temporal extend of movement

Reflection Particle:

$C_i^t, i \in [1:n]$ as 8-connected pixels of the similar motion

Extracted Features: $f(C_i^t) = \{d_i^t, p_i^t, v_i^t\}$

Reflection Particle Matching&Tracking

Matching: *Input:* $f(C_i^t) = \{d_i^t, p_i^t\}$, $f(C_j^{t+\Delta t}) = \left\{d_j^{t+\Delta t}, p_j^{t+\Delta t}\right\}$.

Output: $f(C_i^{t+\Delta t})$.

Tracking: initialized for each detection state transition density:

$$p_i^t = p_i^{i-1} + v_i^{t-1} \times 1, \quad v_i^t = v_i^{t-1}$$

candidate scoring: $err_d^c(c_i^t, cc_i^t) = (d_i^t - dc_j^t)^2$

consider $argmin\left\{err_d^c(c_i^t, cc_j^t\right\}$ as the best track.

trajectories: $T(C_i) = \{p_i^1, p_i^2, ...p_i^t,\}$

Elementary Continuous Surface Segmentation

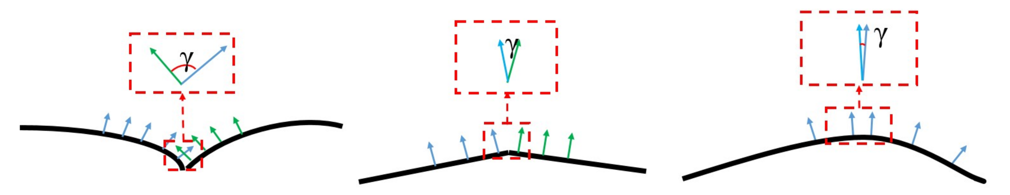
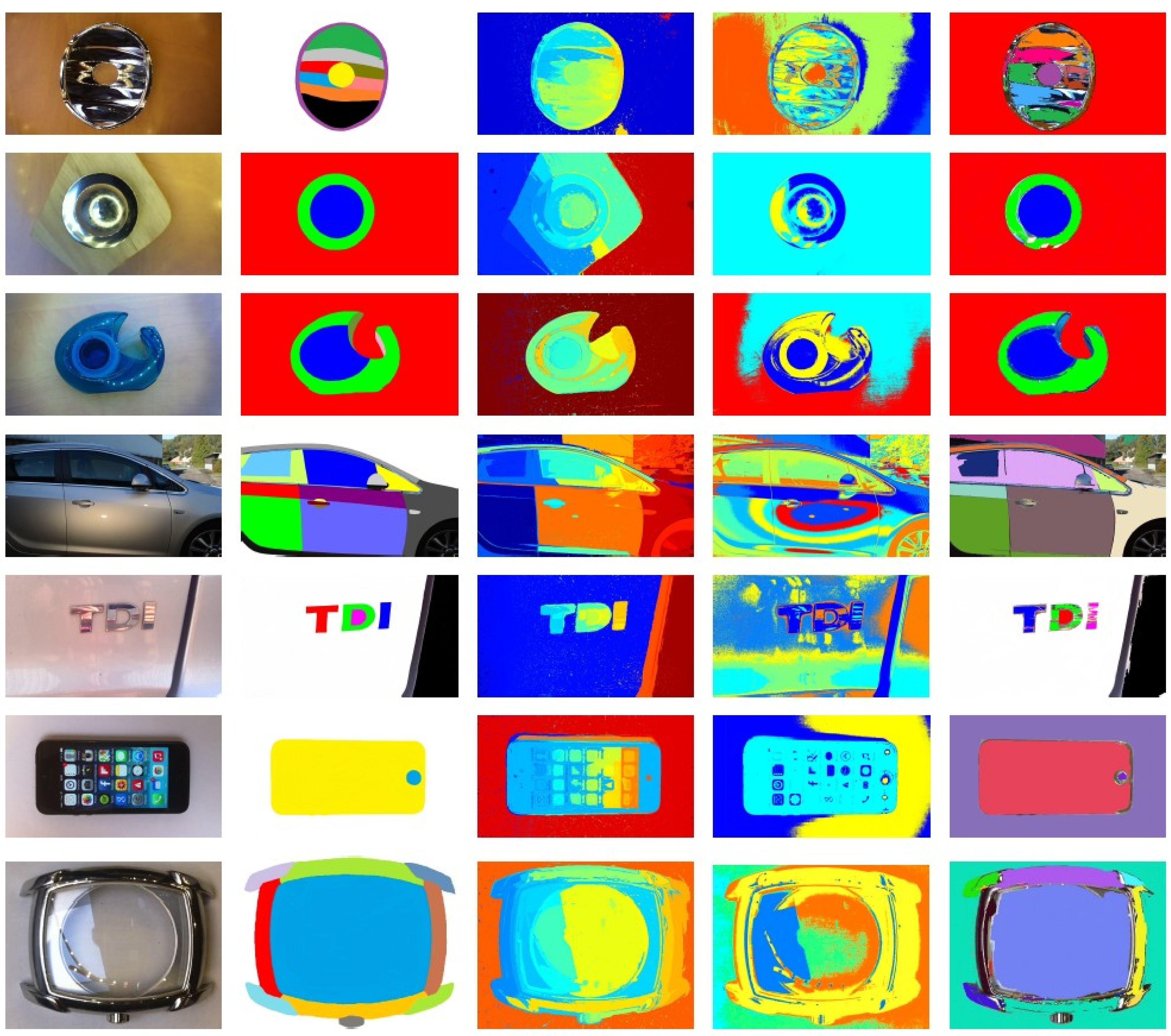


Figure: (1)(2) discontinuous surfaces (3) elementary continuous surface

1. Systematic trajectory sampling with skip 5
2. Segmentation by flood fill algorithm
3. Morphology component regrouping
4. Hole filling with the surrounding label color

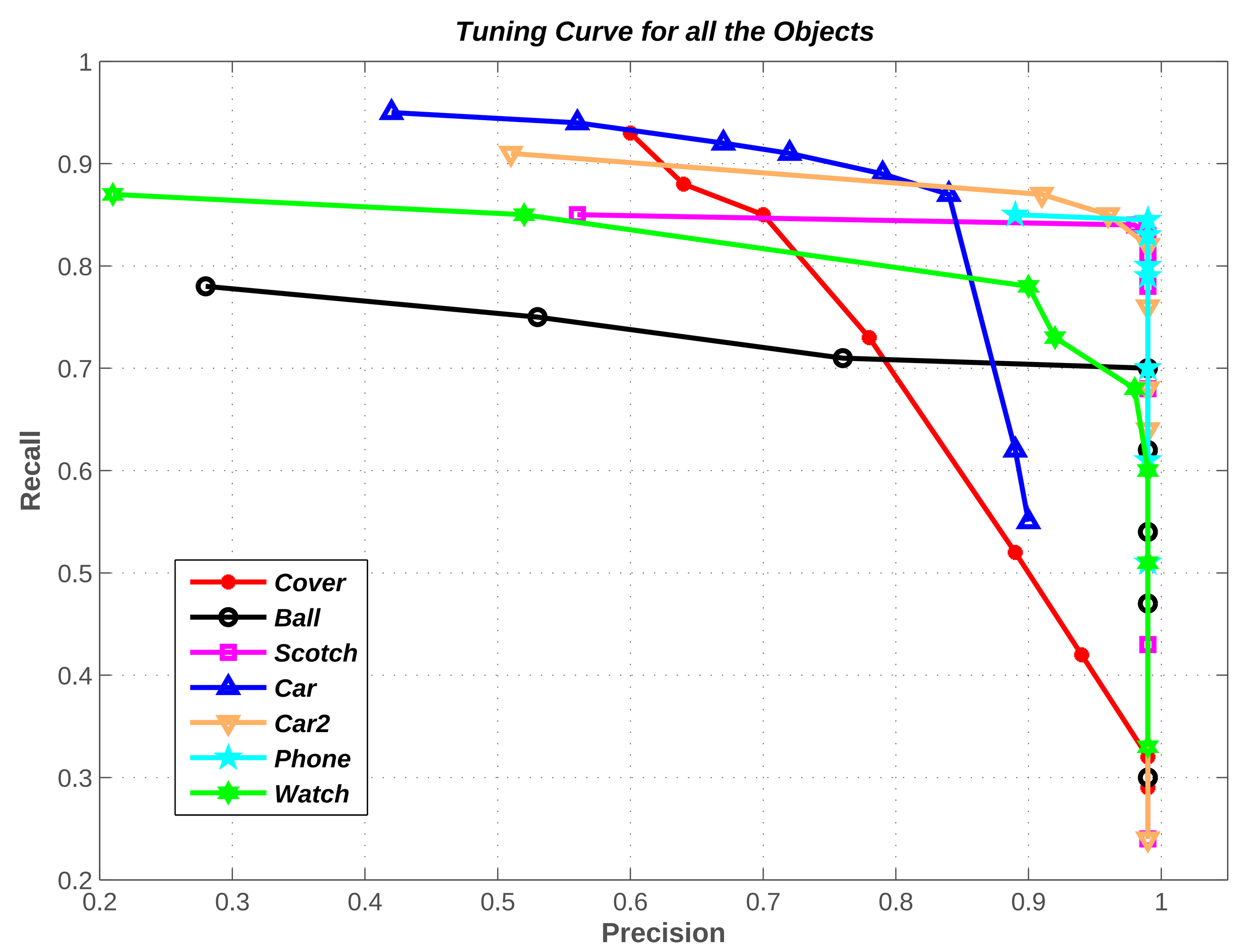
Results and Evaluation

Qualitative Results



first column: orignial image; second column: ground truth segmentation; third column: KNN graph segmentation; forth column: EM segmentation; last column: proposed method.

Quantitative Evaluation



Best f-score of the objects

f-score	Cover	Ball	Scotch	Car	Car2	Phone	Watch
KNN graph	0.56	0.38	0.48	0.73	0.83	0.51	0.74
Ajdacent graph	0.48	0.34	0.54	0.66	0.79	0.48	0.75
EM	0.17	0.41	0.46	0.54	0.27	0.79	0.47
Hierarchical graph	0.46	0.32	0.39	0.72	0.81	0.43	0.44
our method	**0.76**	**0.84**	**0.89**	**0.86**	**0.93**	**0.91**	**0.84**