Comparing Segmentation Algorithms for Automated CHC in Diabetes Self-Management

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Aim of the Work

Carbohydrate counting (CHC) is an established approach in type 1 diabetes, but it depends on patient perception. Automated CHC uses smartphone camera, but runtime and quality of segmentation are crucial for realtime recognition of food items. We Compare runtimes and quality of state-of-art segmentation approaches to separate food items, for food recognition.

Objective of segmentation

To identify and allow further classification of food items in images



Method

Automated CHC uses a smartphone camera to capture image(s) of a meal, then it determines CHC automatically. Segmentation is a crucial step that divides the image into regions that should be food items. We compare Seeded Region Growing (RG-S), Unseeded Region Growing (RG-U), Region Merging (RM), Region Splitting and Merging (RSM), JSEG, K-means Clustering (KMEANS), DBScan (DBSCAN), Edge-based Watershed (W). Some of those:



Description

RG-S: seed on orange, expanding region based on the pixel color values threshold;

RG-U: *n* clusters are created, if difference between pixels scanned and region is less than threshold, add to that region;



Description (cont.)

RM: start each pixel a region, merge based on criteria, goal is to minimize the weighted heterogeneity of the various regions.

RSM: begins by sub-divisions as nested quad-trees. When the splitting criterion is met, the division phase finishes and then merging of sub-regions takes place;

JSEG: color quantization + seeded growing spatial segmentation;

DBSCAN: SLIC divides image into many non-overlapped covering local super-pixels, then density clustering DBSCAN clusters based on spatial+color density of super-pixels.

Best results

JSEG - good comparative performance. Some oversegmentation both in the different fruit shades and shadows and in the background, the banana was correctly segmented and the kiwi segment was acceptable. There is no fragmentation problem and color and texture similarity is really good in the regions found.

- not fast (mean 3.46±1.02; fastest is RSM 0.53±0.03 secs);

DBSCAN - slower than JSEG, with similar visual results. Most of the time consumed is used calculating the superpixels with the SLIC (mean 11.89±0.98);

	Performance on test image	Segment fragmentation	Color similarity	Noise influence
Seeded region growing	Bad	Bad	Acceptable	Bad
Unseeded region growing	Bad	Very bad	Acceptable	Bad
Region merging	Acceptable	Acceptable	Acceptable	Bad
Region splitting and merging	Bad	Bad	Good	Acceptable
JSEG	Good	Good	Good	Good
K-means	Acceptable	Acceptable	Acceptable	Acceptable
DBScan	Good	Acceptable	Good	Acceptable
Watershed algorithm	Bad	Good	Acceptable	Bad

Runtimes:				
RG-S (R= 2.33+-0.16), RG-U (R=585.3+-84), RM (R=19.17+-0.50), RSM (R= 0.53+-0.03), JSEG (R= 3.46+-1.02), KMEANS (R= 3.50+-0.28), DBSCAN (11.89+-0.98),				
VV (R= 2.80+-0.41).				

		User	Execution
		dependency	time
5	Seeded region growing	Bad	Bad
U	nseeded region growing	Good	Very bad
	Region merging	Good	Bad
R	egion splitting and merging	Bad	Very good
	JSEG	Good	Bad
	K-means	Acceptable	Bad
	DBScan	Acceptable	Bad
	Watershed algorithm	Acceptable	Bad

Conclusions

Over-segmentation was constant and shades of color and shadows make segmentation quite difficult. Results appealing to the human eye: JSEG and DBSCAN. However, they require a lot of computation and are slow with large images or in lower capacity handheld devices. The remaining algorithms revealed poor performance.

Future challenges: best feature extraction and classification; speedup algorithms, parallel processing.