Universidad del Valle

Laboratorio de Multimedia y Vision

Classifying Estimated Corresponding Points by Delaunay Triangulation

Presented by

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Content

Laboratorio de Multimedia y Vision

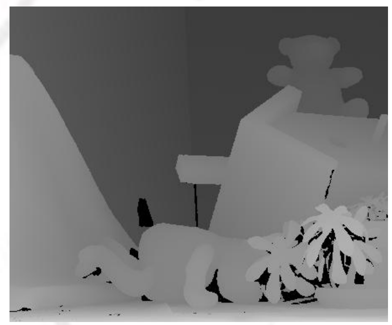
- Stereo Vision
- Applications
- Correspondence Problem
- Objectives
- State of the Art
- Proposed Approach
  - Feature Points
  - Initial Correspondences
  - Delaunay Triangulation
  - Constrains
  - Classification
  - Verification
- Results
- Conclusions

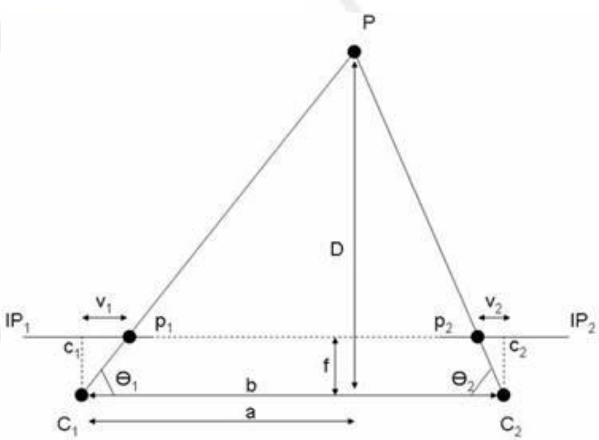
Stereo Vision

Stereo Images → **Correspondence Algorithm** → **Disparity Map** → **Reconstruction Algorithm** → **3D Model**

Left

Right



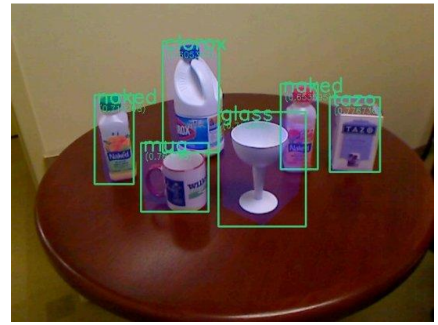


http://vision.middlebury.edu/stereo/data/scenes2003/
http://www.talkingglasses.iblogger.org/?p=603
I. Cabezas, M. Trujillo, M. Florian, On the Impact of the Error Measure Selection in Evaluating Disparity Maps, ISIAC 2012

Applications

Automotive

Entertainment

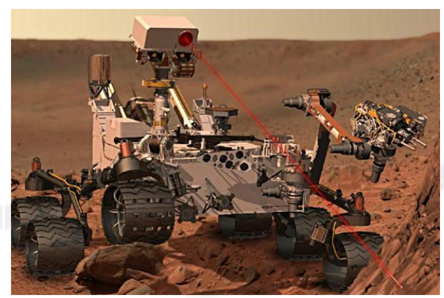


Industry

Medical

Military

Robotics

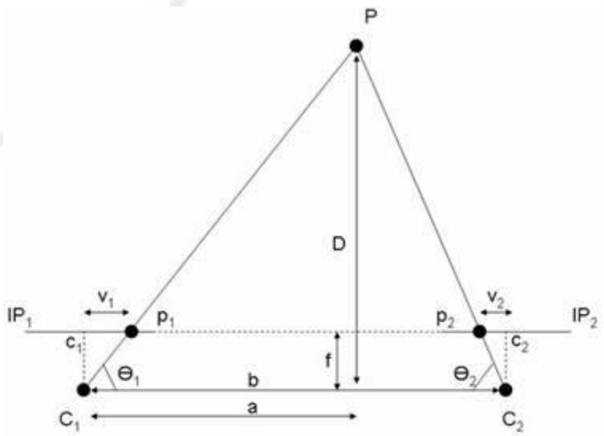


Space

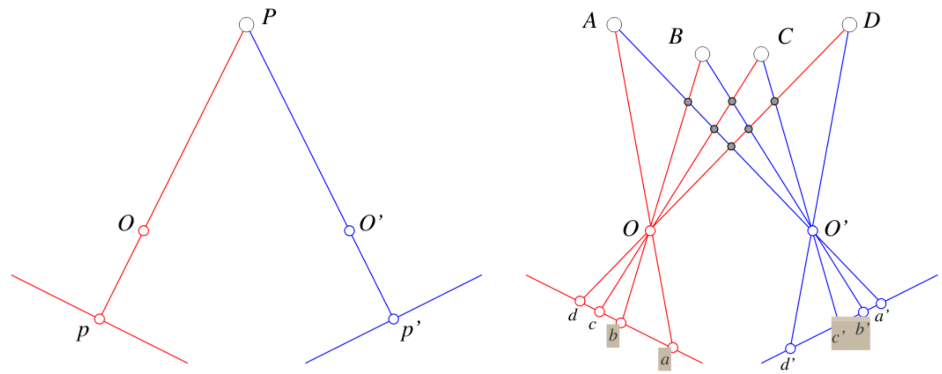
Training

http://news.investors.com/article/618922/201207201352/autonomous-cars-google-self-driving-prius.htm?p=full
http://maoh29.blogspot.com/2010/11/y-que-de-la-realidad-virtual-para.html
http://opencv.willowgarage.com/wiki/GSOC_OpenCV2011
http://ricardogupi.blogspot.com/2010_12_01_archive.html
http://mars.cs.umn.edu/projects/current/PerformanceCLATT/PerformanceCLATT.html
http://mech4eng.blogspot.com/2011/09/robotics.html
http://www.csmonitor.com/Science/2012/0731/Five-essential-facts-about-NASA-s-Mars-Curiosity-rover-video
http://www.hizook.com/blog/2009/08/17/immersive-man-machine-interface-teleoperation-rollin-justin-humanoid-robot

Correspondence Problem

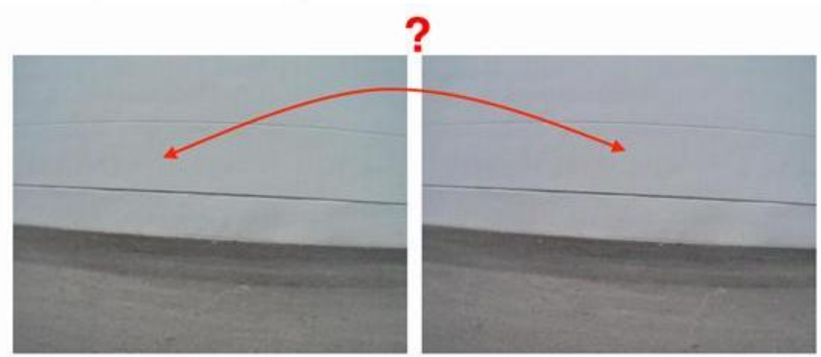


Inverse problem



false-target problem

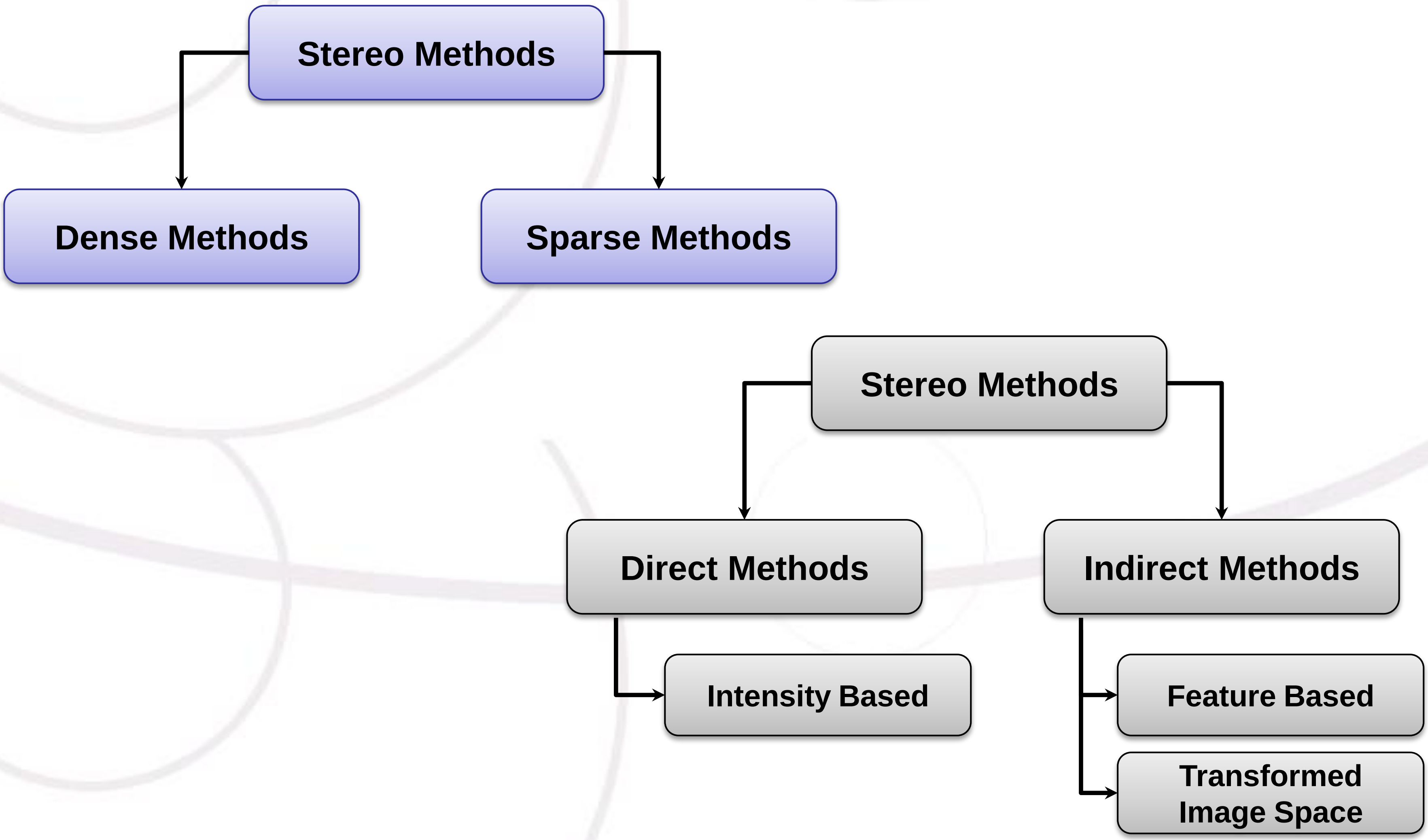
Occlusions



Textureless regions

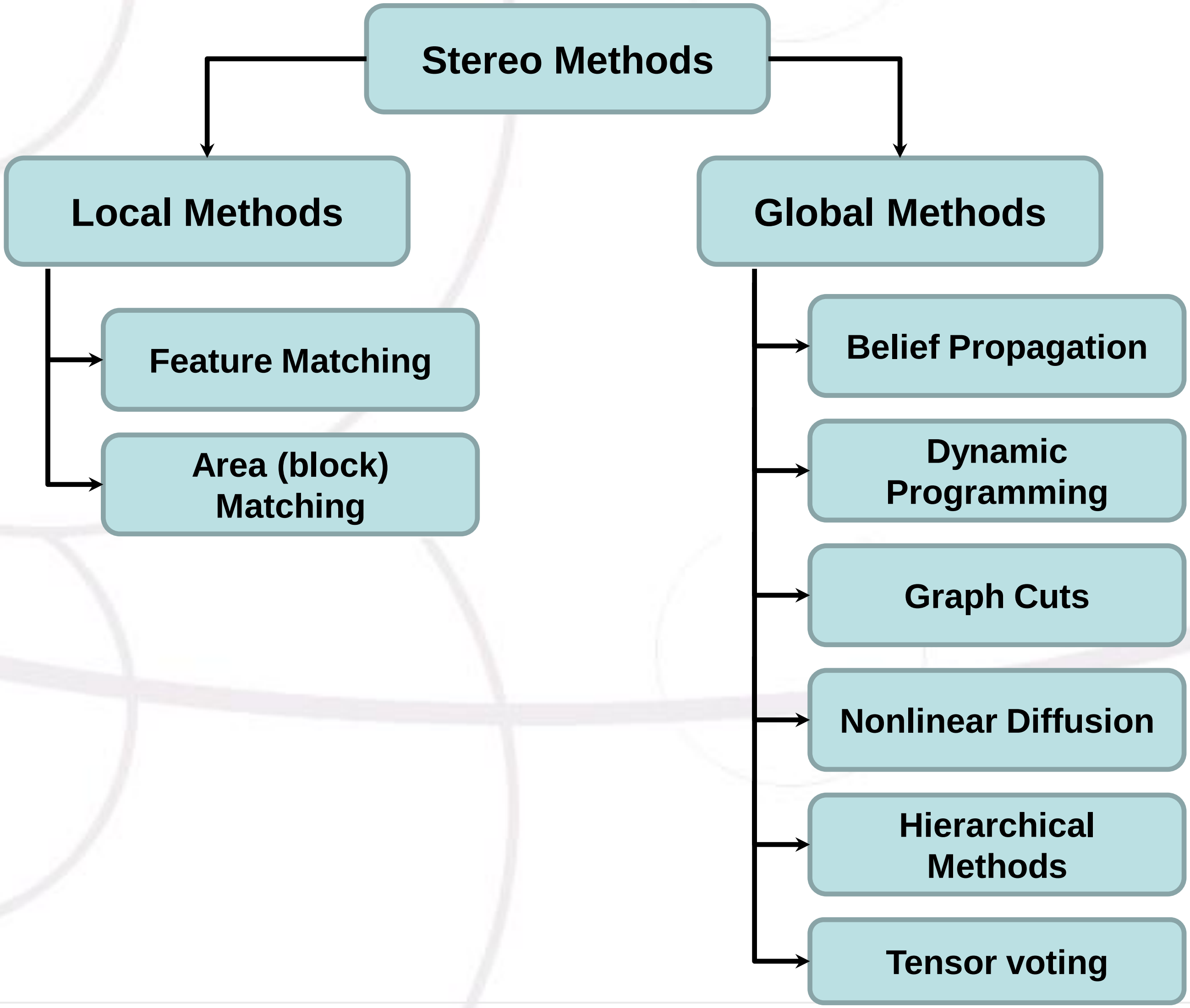
http://www.talkingglasses.iblogger.org/?p=603
John Y. Goulermas. Evolutionary Techniques for the Stereo Correspondence Problem. PhD thesis, University of Manchester, 2000.

State of the Art (I)



J. Paul Siebert Boguslaw Cyganek. An Introduction to 3D Computer Vision Techniques and Algorithms, volume 10. Wiley, 1 edition, February 2009.

State of the Art (II)



J. Paul Siebert Boguslaw Cyganek. An Introduction to 3D Computer Vision Techniques and Algorithms, volume 10. Wiley, 1 edition, February 2009.

State of the Art (III)

- Establishing dense correspondence maps
- Allows estimating large displacements and subsequently taking into account motion/disparity discontinuities
- Computationally efficient

Estimation of large-amplitude motion and disparity fields: Application to intermediate view reconstruction

Efficient Large-Scale Stereo Matching

- Generative probabilistic model
- Bayesian approach
- 2D mesh via Delaunay triangulation

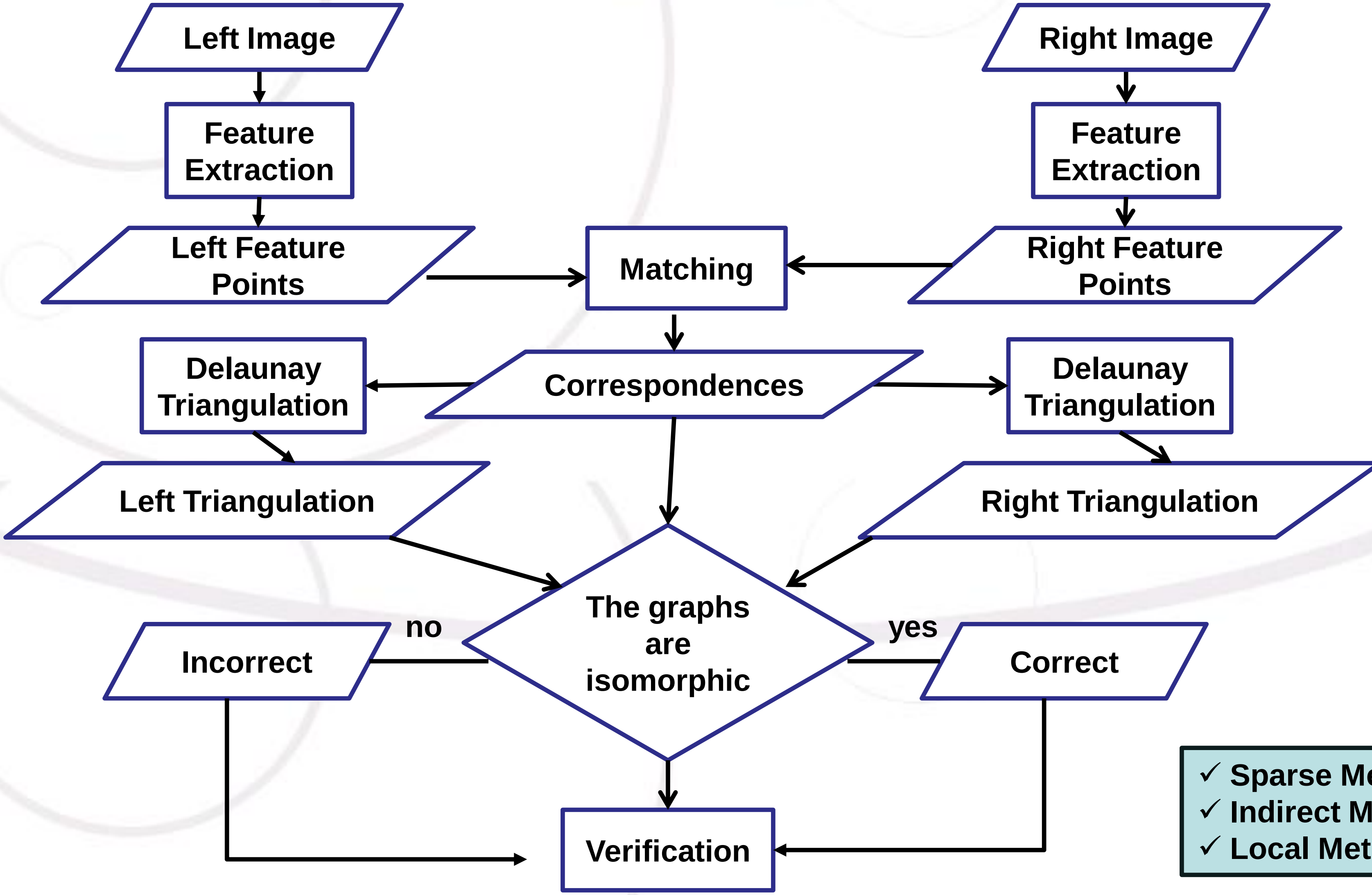
- Image pairs are triangulated
- Triangles are classified into matched and unmatched triangles
- A dense disparity map of the image is obtained

A Dense Stereo Matching Algorithm Based on Triangulation

Effective Corner Matching Based on Delaunay Triangulation

- Input images are partitioned into small and localised regions
- Point correspondences were established by planar homographies

Proposed Algorithm



- ✓ Sparse Method
- ✓ Indirect Method
- ✓ Local Method

Feature Points

Scale Invariant Feature Transform (SIFT)

- Invariant to image scaling and rotation
- Partially invariant to change in illumination and 3D camera viewpoint
- Well localized in both the spatial and the frequency domains
- Reduce the probability of disruption by occlusion, clutter, or noise

Features from Accelerated Segment Test (FAST)

- High quality corner detector
- Implemented using machine learning
- Several orders faster than other corner detectors
- High levels of repeatability under large aspect changes and for different kind of features

Initial Correspondences

Scale Invariant Feature Transform (SITF)

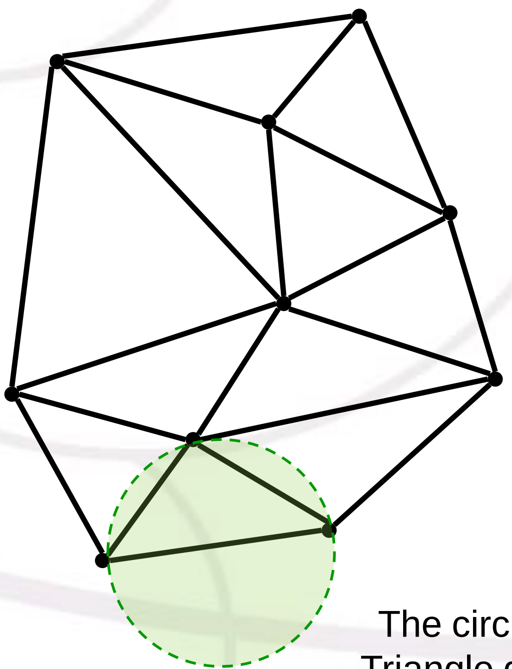
- The matching criteria for the best candidate match for each keypoint is found by identifying its <u>nearest neighbour</u>
- The nearest neighbout is defined as the keypoint with the minimum Euclidean distance for the invariant descriptor vector

Features from Accelerated Segment Test (FAST)

- <u>Block matching strategy using SDD</u> (Sum of squared differences) of the corners descriptor
- The number of matches obtained for each stereo par is variable, but it is around 150 and 300

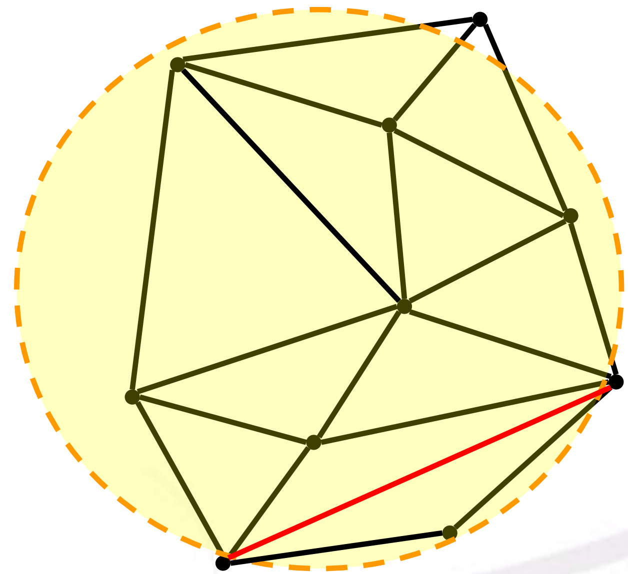
Delaunay Triangulation

It is unique



Maximizes the minimum angle over all triangulations of P

The circumcircle of any Triangle does not contain a point of P in its interior



It is not completely Delaunay

Delaunay Triangulation

Constrained Delaunay Triangulation

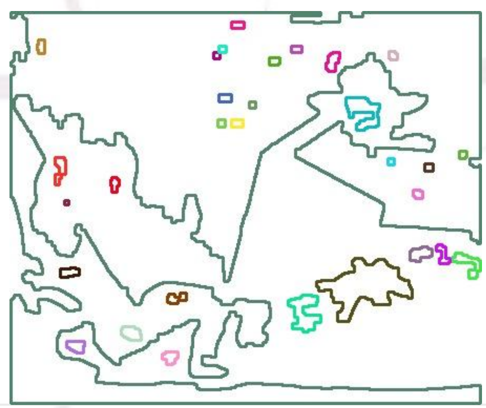
M. De Berg, O. Cheong, and M. Van Kreveld. Computational geometry: algorithms and applications. Springer-Verlag New York Inc, 2008.

Triangles Constrain

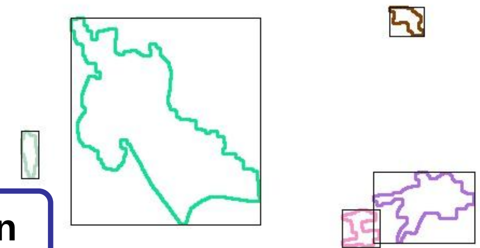
Original image

Threshold + closing + opening

Contours



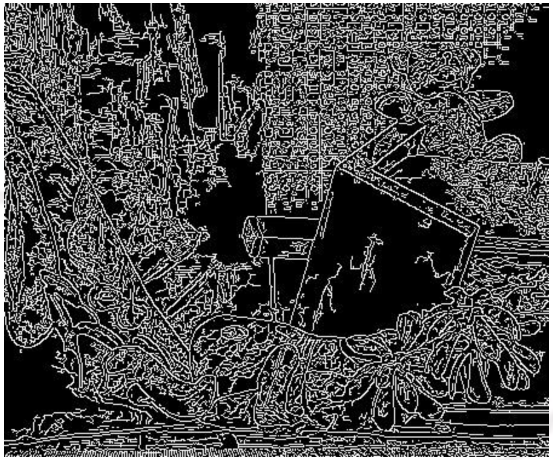
Constrain



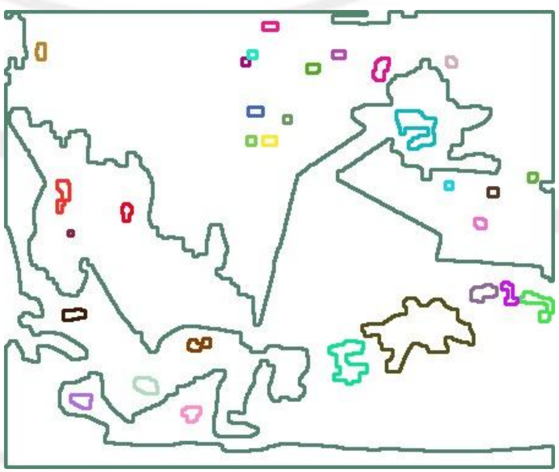
Triangulation

http://vision.middlebury.edu/stereo/data/scenes2003/

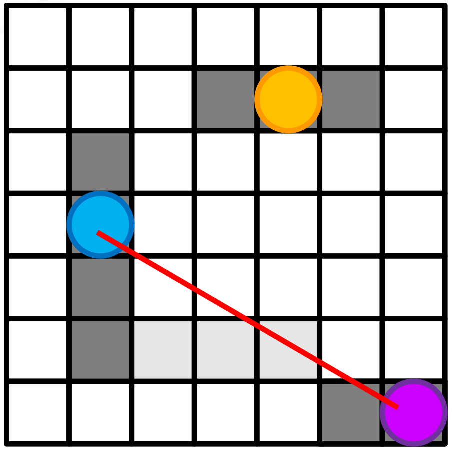
Edges Constrain



Edges

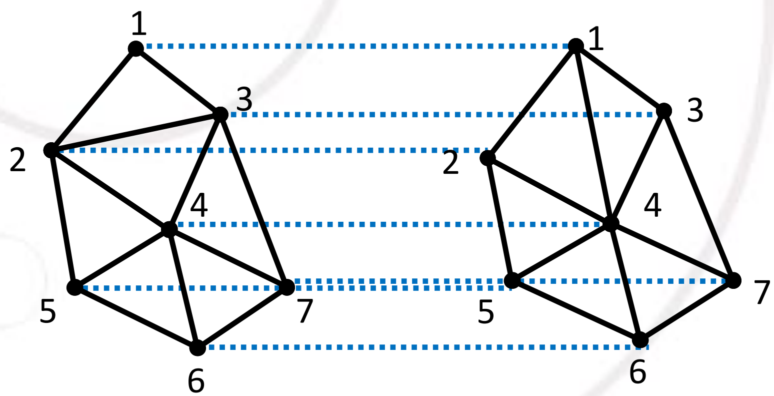


Contours

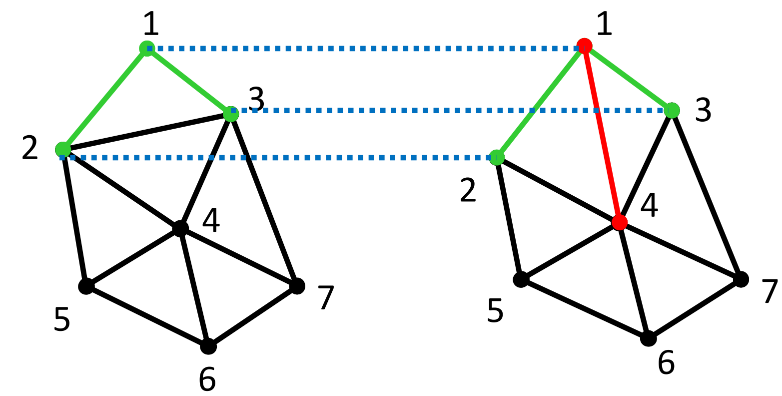


Constrain

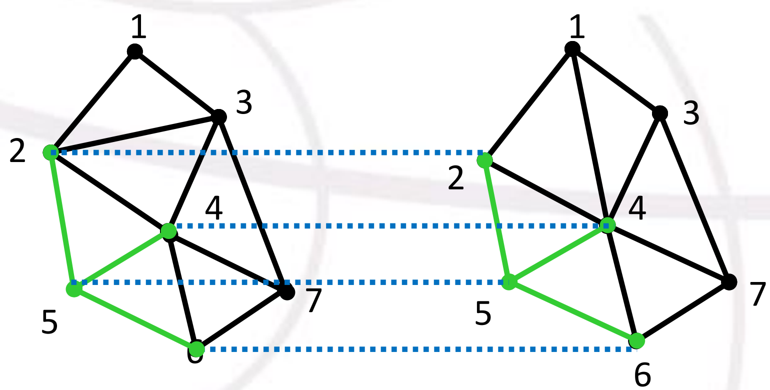
Classification



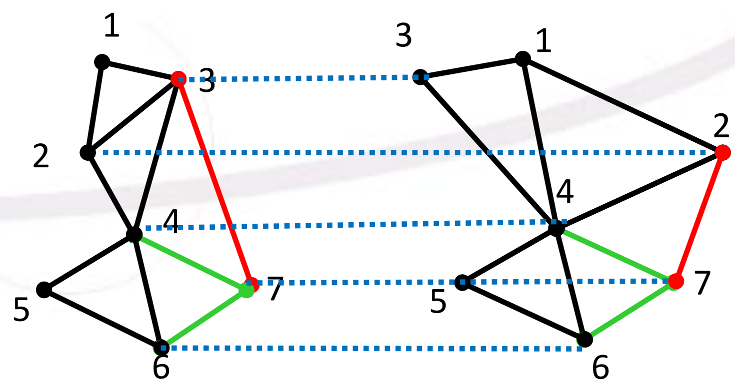
Triangulation of a set of corresponding points



Classification criteria using the vertex number 1



Classification criteria using the vertex number 5



Classification criteria using the vertex number 7

Classification

Given a set of corresponding points, they are mapped into an undirected graph and corresponding points are classified as “correctly estimated” if and only if their graphs are isomorphic

Let G and G’ be a set of corresponding points, from the right and the left images respectively. A Delaunay triangulation produces a set of vertices and edges (V, A) and (V’,A’) respectively. A bijective function f: V → V’ is a graph isomorphism if:

$$w,v,z \in A \leftrightarrow \phi(v), \phi(w), \phi(z) \in A'$$

That is, if *f* preserves the adjacency between vertices,

Thebijective function *f* is represented by the initial map of correspondences and the set of adjacent vertices.

Relaxed Condition

if left.numberOfVertex > 3 **then**

if right.vertex *equal* (left.vertex – 1) **or** right.vertex *equal* left.vertex **then**

mark as correct estimated

else

mark as incorrect estimated

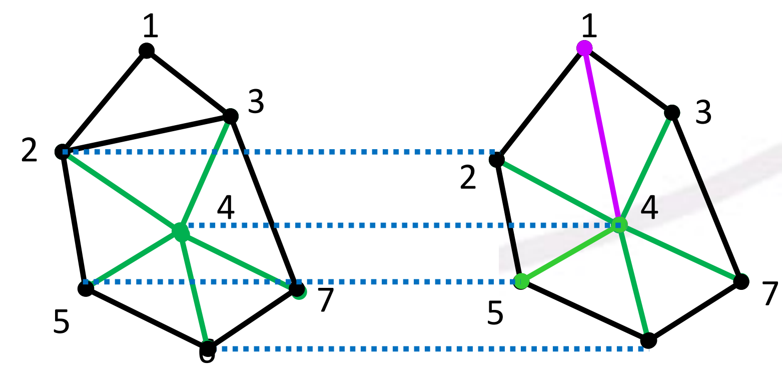
else

if right.vertex *equal* left.vertex **then**

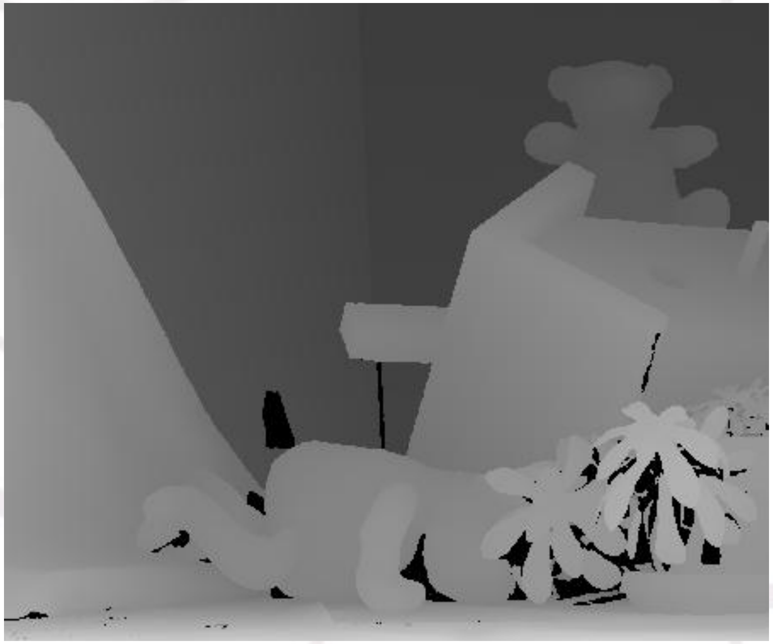
mark as correct estimated

else

mark as incorrect estimated



Verification



Ground Truth Image

$$error_{i,j} = \left| GT_{i,j} - \Delta x_{i,j} \right|$$

$GT_{i,j}$: ground-truth disparity value at (i,j)

$\Delta x_{i,j}$: estimated disparity value at (i,j)

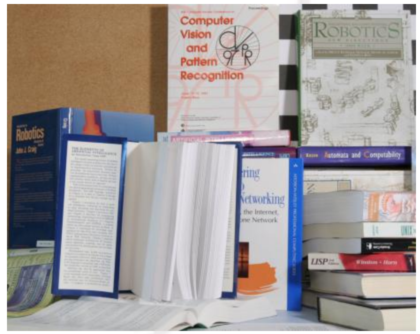
error > 1 : <u>"bad match"</u>

error < 1: <u>"good match"</u>

http://vision.middlebury.edu/stereo/data/scenes2003/

Datasets

Art



Books

Cones

Dolls

Laundry

Moebius

Reindeer

Teddy

http://vision.middlebury.edu/stereo/data/scenes2003/
http://vision.middlebury.edu/stereo/data/scenes2005/

Results

Sensitivity

$$sensitivity = \frac{tp}{tp + fn}$$

Probability that is classified as "bad match", Given that is really a "bad match"

Specificity

$$specificity = \frac{tn}{tn + fp}$$

Probability that is classified as "good match", Given that is really a "good match"

tp: true positives
fp: false positives
tn: true negatives
fn: false negatives

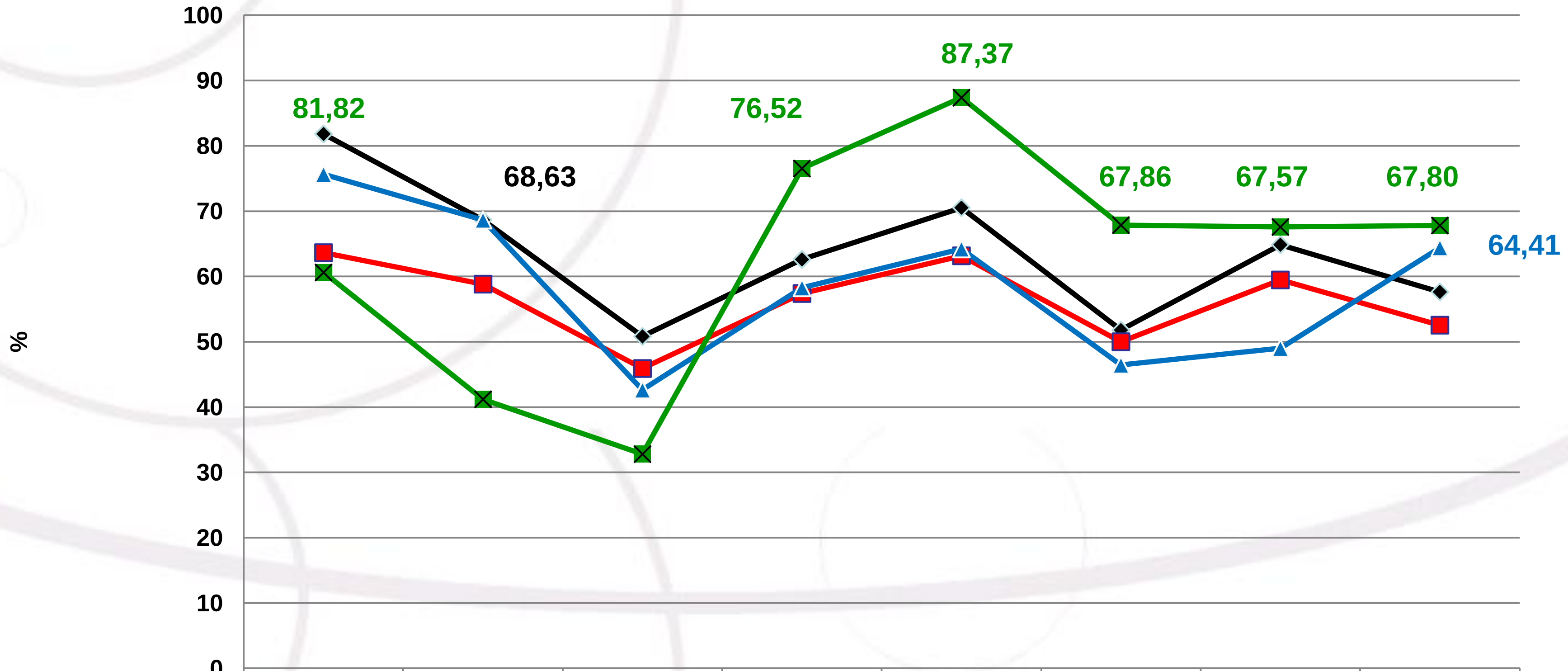
Results: SIFT (I)

SIFT Algorithm Performance (Initial Matching vs Ground-Truth)

Dataset	Points Left	Points Right	Matches	Bad Matches	% Bad Matches
Art	1167	1089	205	33	16,10
Books	823	904	401	51	12,72
Cones	1163	1147	467	61	13,06
Dolls	1462	1406	561	115	20,50
Laundry	1123	1124	263	95	**36,12**
Moebius	867	920	318	56	17,61
Reindeer	592	553	244	37	15,16
Teddy	844	881	328	133	**40,55**

Results: SIFT (II)

Sensitivity for SIFT

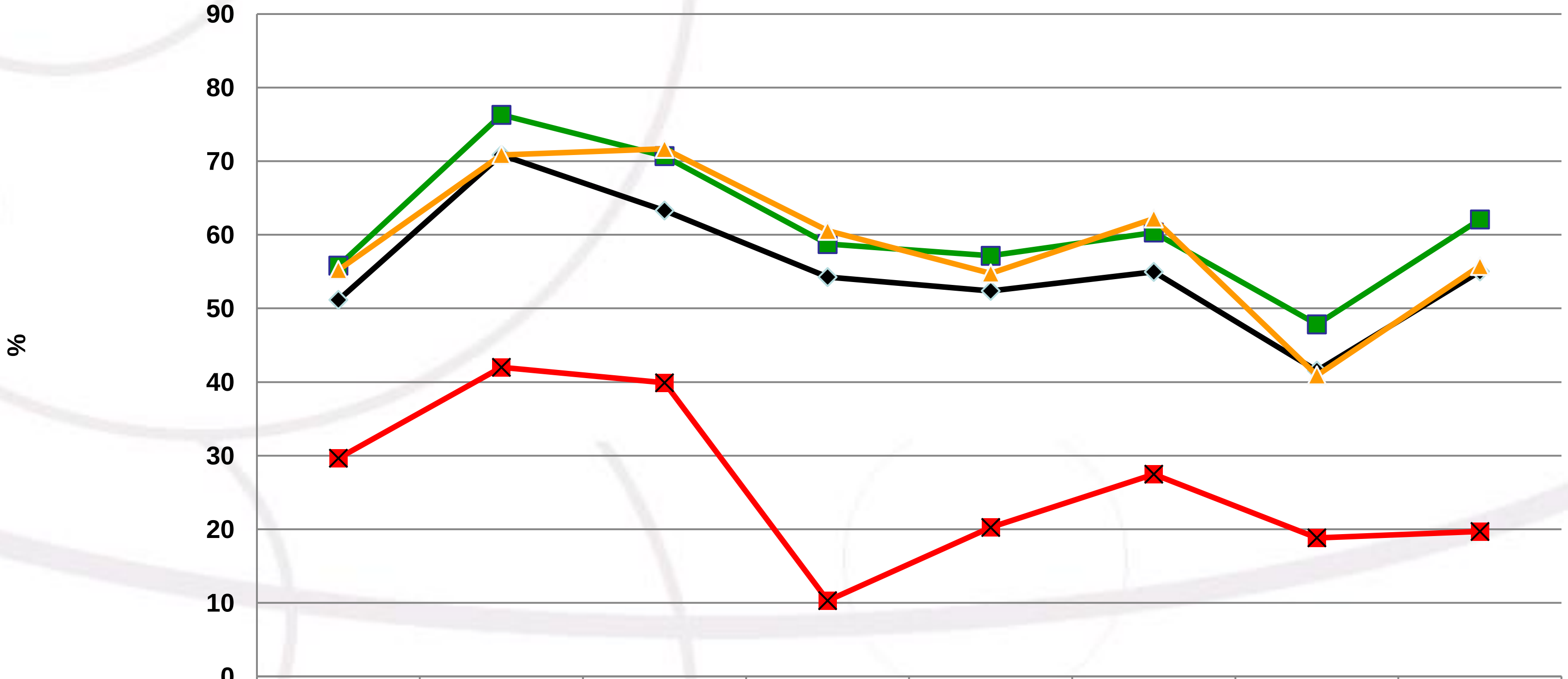


	Art	Books	Cones	Dolls	Laundry	Moebius	Reindeer	Teddy
Sensitivity	81,82	68,63	50,82	62,61	70,53	51,79	64,86	57,63
Sensitivity (r)	63,64	58,82	45,9	57,39	63,16	50	59,46	52,54
Sensitivity (t)	75,65	68,63	42,62	58,26	64,21	46,43	49	64,41
Sensitivity (e)	60,61	41,18	32,79	76,52	87,37	67,86	67,57	67,8

(r) = relaxed condition
(t) = triangles constrain
(e) = edges constrain

Results: SIFT (III)

Specificity for SIFT



	Art	Books	Cones	Dolls	Laundry	Moebius	Reindeer	Teddy
Specificity	51,16	70,86	63,3	54,26	52,38	54,96	41,55	55,02
Specificity (r)	55,81	76,29	70,69	58,74	57,14	60,31	47,83	62,08
Specificity (t)	55,23	70,86	71,67	60,54	54,76	62,21	40,91	55,76
Specificity (e)	29,65	42	39,9	10,31	20,24	27,48	18,84	19,7

(r) = relaxed condition
(t) = triangles constrain
(e) = edges constrain

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Results: Corners (I)

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Corners Algorithm Performance (<u>Initial Matching vs Ground-Truth</u>)

Dataset	Points Left	Points Right	Matches	Bad Matches	% Bad Matches
Art	985	986	164	72	43,90
Books	958	955	303	149	**49,17**
Cones	947	946	268	78	29,10
Dolls	950	948	280	85	30,36
Laundry	960	966	293	194	**66,21**
Moebius	963	970	213	63	29,58
Reindeer	948	955	201	58	28,86
Teddy	950	947	316	123	38,92

Results: Corners (II)

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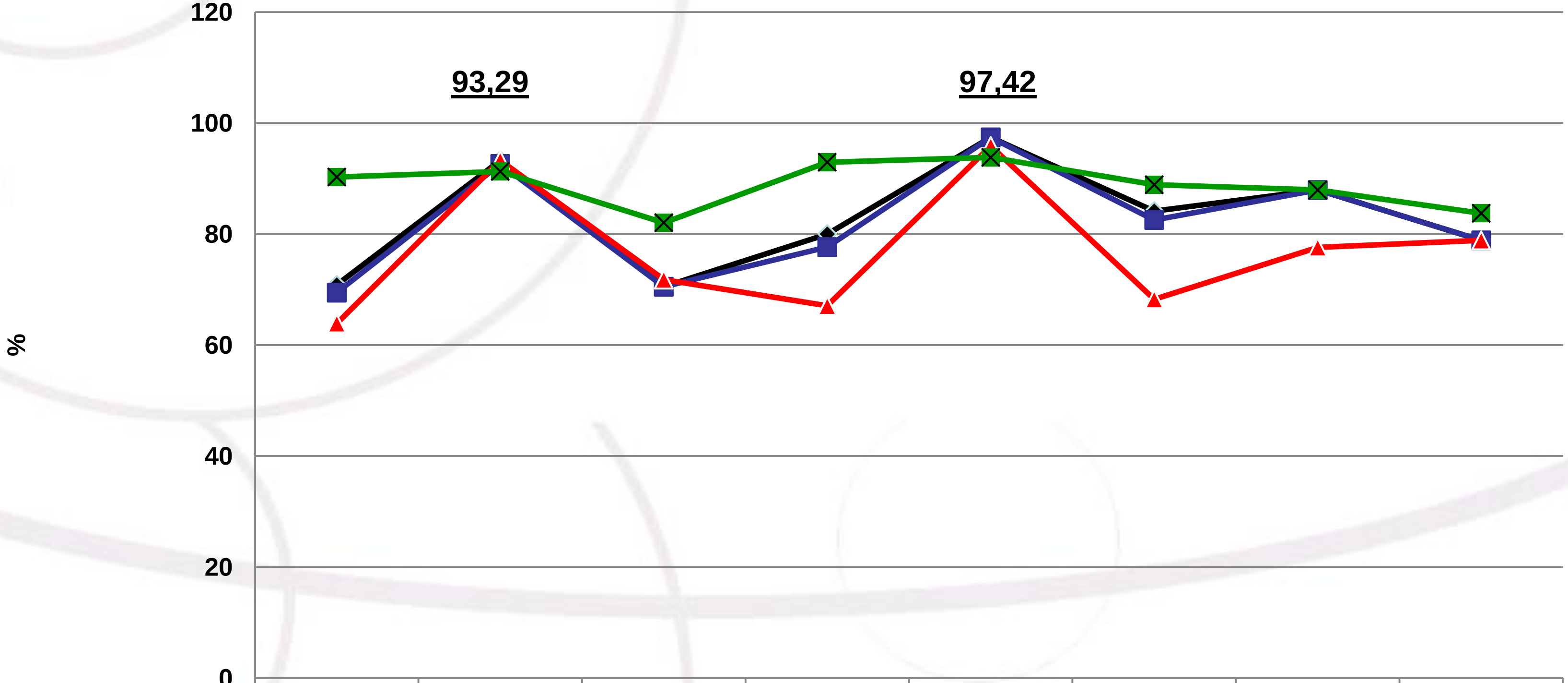
Sensitivity for Corners

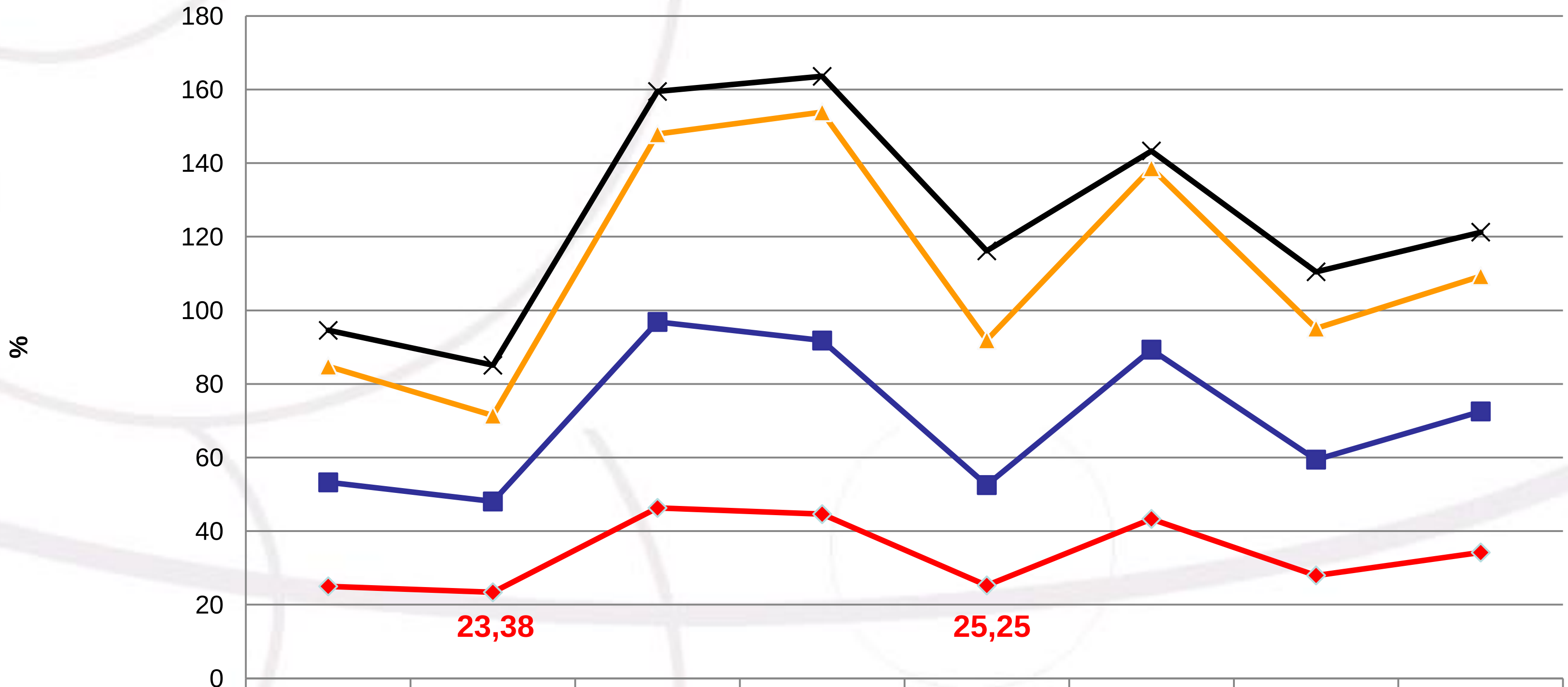


	Art	Books	Cones	Dolls	Laundry	Moebius	Reindeer	Teddy
Sensitivity	70,83	93,29	70,51	80	97,42	84,13	87,93	78,86
Sensitivity (r)	69,44	92,62	70,5	77,65	97,42	82,54	87,93	78,86
Sensitivity (t)	63,89	93,29	71,79	67,06	95,88	68,25	77,59	78,86
Sensitivity (e)	90,28	91,28	82,05	92,94	93,81	88,89	87,93	83,74

(r) = relaxed condition
(t) = triangles constrain
(e) = edges constrain

Results: Corners (III)

Specificity for Corners



	Art	Books	Cones	Dolls	Laundry	Moebius	Reindeer	Teddy
Specificity (e)	9,78	13,64	11,58	9,74	24,24	4,67	15,38	11,92
Specificity (t)	31,52	23,38	51,05	62,05	39,39	49,33	35,66	36,79
Specificity (r)	28,26	24,68	50,53	47,18	27,27	46	31,47	38,34
Specificity	25	23,38	46,32	44,62	25,25	43,33	27,97	34,2

(r) = relaxed condition
(t) = triangles constrain
(e) = edges constrain

Conclusions

- The use of all the recognized keypoints for the triangulation, **adds noise** to it

- The classification algorithm **presents better performance for the corners than for the SIFT keypoints**, in terms of **sensitivity**, which is for our analysis the most representative measurement of quality. On the other hand, the **specificity is higher for the SIFT algorithm**

- The classification algorithm exhibit the **best performance** in the **corners feature points**, where the percentage of initial bad matches is bigger than approximately **50%.** It means, that the algorithm presents **high sensitivity** (between 93% and 97%) **when the initial matching is bad**

- The use of **constrains** contribute to the **increment of specificity**. However, it also **decrements the sensitivity**

- The **relaxed evaluation condition** presented **worked better** for the **corners features**, because of the locations of the points