



TOPICS IN VIRTUAL REALITY: MATHEMATICAL METHODS FOR VISUAL COMPUTING

EXERCISE 3 - GLOBAL OPTIMIZATION

Handout date: 18 October 2017
Submission deadline: 1 November, 17:59
Demo date: TBA

GENERAL RULES

Plagiarism note. Copying code (either from other students or from external sources) is strictly prohibited! We will be using automatic anti-plagiarism tools, and any violation of this rule will lead to expulsion from the class.

Late submissions will not be accepted, except in case of serious illness or emergency. In that case please notify the teaching assistants.

Software. All exercises of this course use the MATLAB programming language. The MATLAB distribution is available from <http://kftp.kaist.ac.kr/> for KAIST students. See our MATLAB tutorial slides for hints or specific functions that could be useful for your implementation.

What to hand in. Submit a .zip file of your solution on KLMS. The *zip file* must be called “MathMethods17-Ex*-firstname-familyname.zip” (replace * with the assignment number, e.g. MathMethods17-Ex01-John-Smith.zip). The .zip file **MUST** contain *a single folder* with the following data inside:

- A folder named “code” containing your MATLAB code
- A README file (in pdf format) containing a description of what you have implemented and instructions for running it, as well as explanations/comments on your results.
- Screenshots of all your results with associated descriptions in the README file.

Grading. The homeworks count for 70% of your total grade. Your homework submission will be graded according to the quality of the images/results produced by your program, the conformance of your program to the expected behaviour of the assignment, and your understanding of the underlying techniques used in the assignment. The submitted code must produce exactly the same images included in your submission.

To ensure fairness of your grade, you will be asked to briefly present your work to the teaching assistants. Each student will have about 5 minutes to demo their submission and explain in some detail what has been implemented, report potential problems and how they tried to go about solving them, and point the teaching assistants to the code locations where the various key points of the assignments have been implemented. See above for the scheduled demo date for this particular assignment.

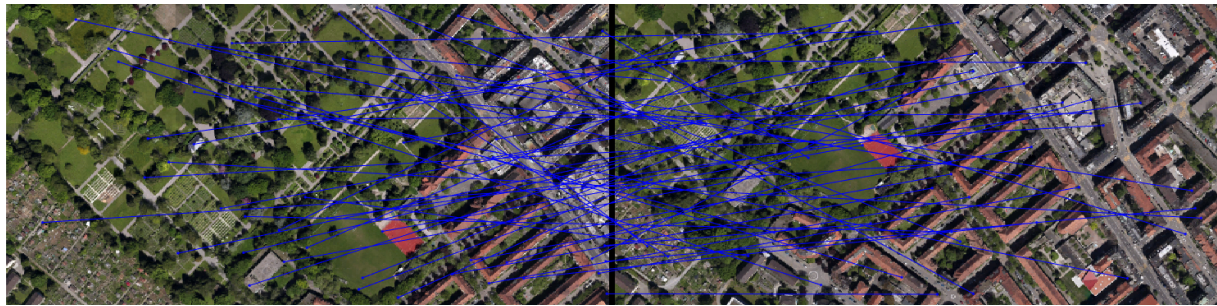
GOAL OF THIS EXERCISE

In this exercise you will apply what you learned about global optimization, especially branch and bound (B&B), concave and convex envelopes, reformulation, and Linear Programming. You will implement, in Matlab, branch and bound for consensus set maximization.

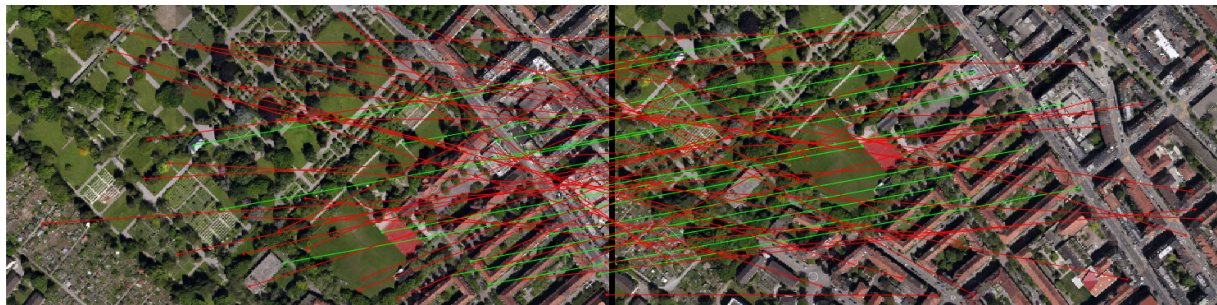
Read the whole exercise sheet before starting!

1. EXERCISE: BRANCH AND BOUND FOR CONSENSUS SET MAXIMIZATION

Context and goal. In the context of stereo matching, you will implement consensus set maximization by branch and bound where the model is a 2D translation between two input images. We provide the left and right images, and a set of 2D correspondences composed of inliers and outliers (see Figure 1(a)). The images are related by a 2D translation. Given this input set of correspondences, the goal is to maximize the consensus set (i.e. maximize the number of inlier correspondences), identify the inlier and outlier correspondences, and estimate the model (2D translation). The identified inliers and outliers are shown in Figure 1(b).



(a)



(b)

FIGURE 1. (a) input correspondences (b) the inlier and outlier correspondences obtained by branch and bound.

As seen in the lecture, the consensus set maximization problem can be formulated as follows. Let the set S of the input data be partitioned into an inlier-set $S_I \subseteq S$ and an outlier-set $S_O = S \setminus S_I$.

The cardinality of S_I corresponds to the number of detected inliers. Let q_i represent the i -th data point/sample/information/feature, and Θ be the unknown underlying model. The general consensus set maximization can be mathematically formulated as:

$$\begin{aligned} (1a) \quad & \max_{\Theta, S_I} \quad \text{card}(S_I) \\ (1b) \quad & \text{s.t.} \quad f(\Theta, q_i) \leq \delta, \forall i \in S_I \subseteq S \end{aligned}$$

This formulation simply states that, given a residual tolerance δ (the inlier threshold), the goal is to find the largest consensus set (i.e. maximize the number of inliers) under a model Θ and to estimate this model.

In our context of 2D translation with correspondences between two images, we note:

- the model $\Theta = T = (T_x, T_y)$ where T_x and T_y represent the translation along the x and y axis.
- the i -th input correspondence (p_i, p'_i) where p_i and p'_i represent the points in the left and right images. Their x and y coordinates are written $p_i = (x_i, y_i)$ and $p'_i = (x'_i, y'_i)$. We have n input correspondences, i.e. $i = 1, \dots, n$
- the cost function f is composed of two parts: error on the x axis and error on the y axis:

$$(2a) \quad f_x(\Theta, p_i, p'_i) = |x_i + T_x - x'_i|$$

$$(2b) \quad f_y(\Theta, p_i, p'_i) = |y_i + T_y - y'_i|$$

A correspondence (p_i, p'_i) is considered inlier if the x and y residuals are below the inlier threshold:

$$(3) \quad |x_i + T_x - x'_i| \leq \delta \text{ and } |y_i + T_y - y'_i| \leq \delta$$

Our consensus set maximization problem can now be formulated as:

$$\begin{aligned} (4a) \quad & \max_{\Theta, S_I} \quad \text{card}(S_I) \\ (4b) \quad & \text{s.t.} \quad f_x(\Theta, p_i, p'_i) \leq \delta, \forall i \in S_I \subseteq S \\ (4c) \quad & f_y(\Theta, p_i, p'_i) \leq \delta, \forall i \in S_I \subseteq S \end{aligned}$$

i.e.

$$\begin{aligned} (5a) \quad & \max_{\Theta, S_I} \quad \text{card}(S_I) \\ (5b) \quad & \text{s.t.} \quad |x_i + T_x - x'_i| \leq \delta, \forall i \in S_I \subseteq S \\ (5c) \quad & |y_i + T_y - y'_i| \leq \delta, \forall i \in S_I \subseteq S \end{aligned}$$

What we provide. We provide you:

- the input left and right images: see InputLeftImage.png and InputRightImage.png
- a set of correspondences composed of inliers and outliers. see ListInputPoints.mat. Its size is $n \times 4$ where n is the number of input correspondences. The i -th row contains the coordinates of the points of the i -th correspondence: (x_i, y_i, x'_i, y'_i) . You can load it with `load('ListInputPoints.mat', 'ListInputPoints')`.

- the inlier threshold $\delta = 3$ pixels.

REQUIRED DELIVERABLES

You will provide the following deliverables:

- Derivation of the problem formulation in the canonical form of Linear Programming (see Section 2). In the report, you can write down the derivations in LaTeX, MS Word or simply by hand (take a picture).
- The matlab code implementing branch and bound for consensus set maximization with a 2D translation model
- The results of the translation model (i.e. the values of T_x and T_y), and the indices of the inliers and outliers obtained by branch and bound
- A figure showing the identified inlier and outlier correspondences, like Figure 1(b)
- A figure showing the convergence of the cardinality bounds, i.e. the highest lower bound obtained so far, and the highest upper bound still in the list. See Fig. 2.

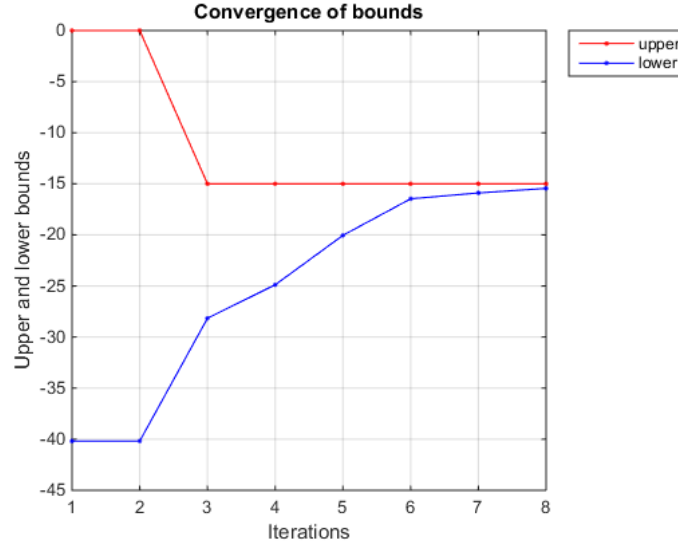


FIGURE 2. Evolution of the lower and upper bounds of the number of inliers along the branch and bound iterations.

2. HINTS AND NOTATION

Here is some additional information to help you with branch and bound:

- the model Θ is 2D translation (T_x, T_y) . Lets note the lower and upper (definition) bounds of Θ as $\underline{T}_x, \overline{T}_x, \underline{T}_y, \overline{T}_y$.
- given a space of Θ (i.e. $T_x \in [\underline{T}_x, \overline{T}_x]$ and $T_y \in [\underline{T}_y, \overline{T}_y]$)

- compute the upper bound of the nb of inliers by solving the LP
- compute the lower bound of the nb of inliers by simply testing the model Θ obtained by LP (it is inside the current definition space) or a specific Θ in the space, for example the one at the center, i.e. test $\Theta = (T_x, T_y) = ((\underline{T}_x + \overline{T}_x)/2, (\underline{T}_y + \overline{T}_y)/2)$.
- conduct a depth-first search: at each iteration take the best candidate in the list, split it into two children, compute their cardinality bounds, and remove all the elements in the list with a “bad” bound. When you take the best candidate, remove it from the list, and put its two children into the list
- iterate and remove the spaces that definitely do not contain the optimal solution. For example, let m^* be the highest lower bound of the number of inliers obtained so far. If the upper cardinality bound of a space is less than m^* , it can be safely removed, because even in the best case it cannot contain a better solution.
- when branching, split the current space into two children subspaces in half along the longest dimension
- the iterations stop when the lower and upper bound are nearer than 1, because they will lead to the same integer number of inliers

Reformulation. The first task is to reformulate Eq. (5a) to obtain a linear programming. For this, as seen in the lecture:

- introduce the identification binary variable z_i with $i = 1, \dots, n$. Let $z_i = 1$ if the i -th correspondence is an inlier, i.e. if $f_x(\Theta, p_i, p'_i) \leq \delta$ and $f_y(\Theta, p_i, p'_i) \leq \delta$. Otherwise $z_i = 0$, i.e. the i -th correspondence is an outlier.
- relax the binary variables z_i
- to avoid the bilinear terms, introduce the auxiliary variables $w_{ix} = z_i T_x$ and $w_{iy} = z_i T_y$
- replace the bilinear terms using the concave and convex envelopes
- reformulate the constraints containing absolute terms, i.e. $|a| \leq b \Rightarrow a \leq b$ and $-a \leq b$
- write down the final linear program system in canonical form

Implementation hints. Here are some implementation hints (feel free to use or ignore them):

- create a list that contains the lower and upper (definition) bounds of Θ , i.e. $\underline{T}_x, \overline{T}_x, \underline{T}_y, \overline{T}_y$, and its lower and upper cardinality bounds. The list can be a structure with the fields ThetaLowerBound (i.e. $(\underline{T}_x, \underline{T}_y)$), ThetaUpperbound (i.e. $(\overline{T}_x, \overline{T}_y)$), ObjLowerBound (lower bound of the nb of inliers, obtained by testing a certain model), ObjUpperBound (upper bound of the nb of inliers, obtained by LP, “obj” stands for objective function), ThetaOptimizer (the model obtained by LP).
- for LP,
 - we have a long unknown vector that is the concatenation of Θ , \mathbf{z} and \mathbf{w} . If we note \mathbf{x} the unknown vector of LP, then we have something like $\mathbf{x} = (\Theta, \mathbf{z}, \mathbf{w})$, for example:

$$(6) \quad \mathbf{x} = (T_x, T_y, z_1, \dots, z_n, w_{1x}, w_{1y}, \dots, w_{nx}, w_{ny})$$

or for example:

$$(7) \quad \mathbf{x} = (T_x, T_y, z_1, \dots, z_n, w_{1x}, \dots, w_{nx}, w_{1y}, \dots, w_{ny})$$

– construct c , A and b , and build the canonical form (in Matlab for linprog):

$$\begin{aligned} (8a) \quad & \min_{\mathbf{x}} c^T \mathbf{x} \\ (8b) \quad & \text{s.t. } A\mathbf{x} \leq b \\ (8c) \quad & \text{and } l_b \leq \mathbf{x} \leq u_b \end{aligned}$$

- to compute the lower bound with LP, create a function whose inputs are the definition bounds of Θ , the data points and the inlier threshold, and returns the LP results, i.e. the optimized model Θ and the objective cost (the floating point (not integer) sum of the relaxed z_i)
- We will not grade the execution speed, but here are some hints if you want to have a fast execution. Matlab can be slow when the matrix size increases, so set the matrix size at the beginning, for example the matrix A and b of the linear programming. Note also that some parts of the matrix are always the same throughout the iterations (i.e. the equations independent of the Θ space bounds), so instead of setting them at each new iteration, you can set them only once during the initialization. Matlab can also be slow with loops. Below are some matlab functions you can use to avoid loops. Again, we will not grade the execution time. A reasonable implementation will run in less than 30 seconds. A very naive implementation might run in minutes.
- some matlab functions you can find useful:
 - use sparse matrices: `sparse(H,W)` for zeros and `speye(H)` for identity matrix
 - `deal`. For example $X = [1, 2, 3]$, $N = 5$, $Cells = cell(1, N)$, $[Cells\{:}\}] = deal(X)$; and each cell of `Cells` will contain X
 - `blkdiag`. $M = blkdiag(4, 2, 1, 3)$,

$$(9) \quad M = \begin{bmatrix} 4 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 3 \end{bmatrix}$$

but also with cells: $X = [1, 2]'$, $N = 3$, $Cells = cell(1, N)$, $[Cells\{:}\}] = deal(X)$, $blkdiag(Cells\{:}\})$

$$(10) \quad M = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 2 \end{bmatrix}$$

Linear Programming (not graded). This part is not graded. It is only meant to help you get familiar with setting up a linear programming system.

For example, solve the following Linear Programming using linprog:

$$\begin{aligned}
 (11a) \quad & \min_{x_1, x_2, x_3} 3x_1 + -7x_2 + 9x_3 \\
 (11b) \quad & \text{s.t. } 3x_1 + 4x_2 + 8x_3 \leq -12 \\
 (11c) \quad & x_1 + 2x_2 + -7x_3 \leq 3 \\
 (11d) \quad & -5 \leq x_i \leq 7 \text{ for } i = 1, \dots, 3
 \end{aligned}$$

The following example needs conversion to use linprog (note the max, the inequality signs, and that some variables do not exist in all the constraints):

$$\begin{aligned}
 (12a) \quad & \max_{x, y, z} 3x - 2y + 4z \\
 (12b) \quad & \text{s.t. } 4x - z \geq -3y + 12 \\
 (12c) \quad & 5x \leq 4 + z \\
 (12d) \quad & 0 \leq x \leq 3, 4 \leq y, 1 \leq z \leq 7
 \end{aligned}$$