Application

2015-03-31

2015-05098	Oskarsson, Magnus	NT-14

Information about applicant

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Information about application

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Keywords: Computer vision, structure-from-motion-estimation, sensor fusion, robust estimation

Funds applied for

Year:	2016	2017	2018	2019
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Participants

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Descriptive data

Project info

Project title (Swedish)*

Kamera- och 3D-geometriskattningar från bilddata med ytterligare sensor-data

Project title (English)*

Camera and 3D Geometry from images using additional sensor data

Abstract (English)*

In this project we will investigate geometric estimation problems in computer vision. i.e estimating camera and 3D geometry from image mesurements.
The first step in a typical pipeline for reconstruction is to extract features from the images, with corresponding feature descriptors.
The second step is an initial matching of features from different images. From these matchings the geometry is estimated, often using some robust estimation algorithm such as RANSAC.
The final step is usually a non-linear refinement of the solution, so called bundle adjustment.
In all the steps we have to consider both gross errors in our measurements (outliers) and errors following some error distribution (e.g. normally distributed with some standard deviation).
We will in this project try to incorporate additional sensor data, that is often available in conjunction with image data, e.g. GPS or accelerometer measurements.
The goal is to incorporate this extra information in all steps of the reconstruction pipeline, in order to (i) make the final solution more robust to gross errors, (ii) make the final solution more accurate and (iii) to make the estimation process faster.

Popular scientific description (Swedish)*

Säg att du befinner dig i en okänd stad, och vill veta var du befinner dig. I detta projekt undersöker vi hur man kan lösa detta problem med hjälp av kameror. Detta är ett delproblem inom vad som kallas för datorseende. Givet en eller flera bilder vill vi kunna bestämma var bilden är tagen (kamerans position) och i vilken vinkel (kamerans rotation). För att denna position skall vara meningsfull måste den kunna relateras till någon form av karta av omgivningen. Ett sätt att representera en sådan karta är med hjälp av ett antal kända 3D-punkter, en så kallad 3D rekonstruktion av verkligheten. I dagens läge finns det automatiska metoder för att både räkna ut ett antal kamerors position samt en stor mängd av de punkter som avbildas i bilderna. Dock fungerar dessa metoder ej i alla fall, och de kan ta väldigt lång tid på sig att räkna ut lösningen. I detta projekt tänker vi oss att man använder extra sensorinformation som ofta finns tillgänglig när man tar bilder, såsom riktningsdata från accelerometrar eller positionsmätningar från GPS. Genom att använda sådan information i kombination med bilder kan vi skapa metoder som är mer robusta, mer noggranna samt snabbare. För att lösa dessa problem använder vi moderna matematiska metoder baserade på modellering, optimering och algebraisk geometri.

Project period

Number of project years*

4

Calculated project time*

2016-01-01 - 2019-12-31

Classifications

Select a minimum of one and a maximum of three SCB-codes in order of priority.

Select the SCB-code in three levels and then click the lower plus-button to save your selection.

SCB-codes*

1. Naturvetenskap > 102. Data- och informationsvetenskap (Datateknik) > 10207. Datorseende och robotik (autonoma system)

1. Naturvetenskap > 101. Matematik > 10102. Geometri

2. Teknik > 202. Elektroteknik och elektronik > 20201. Robotteknik och automation

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Enter a minimum of three, and up to five, short keywords that describe your project.

Keyword 1*

Computer vision

Keyword 2*

structure-from-motion-estimation

Keyword 3*

sensor fusion

Keyword 4

robust estimation

Keyword 5

Ethical considerations

Specify any ethical issues that the project (or equivalent) raises, and describe how they will be addressed in your research. Also indicate the specific considerations that might be relevant to your application.

Reporting of ethical considerations*

There are no apparent ethical questions that relate directly to the project. There is no handling of personal data, and no animal or human trials. The dataset that will be used in the project has been processed so that faces and license plates are blurred.

The project includes handling of personal data

No

The project includes animal experiments

No

Account of experiments on humans

No

Research plan

Research Programme

Purpose and aims

> We choose to go to the moon in this decade and do the other things, not because they are easy, but because they are hard.
>
> John F. Kennedy 1962.

We should address hard questions in research, but in order to solve hard problems we should use all available information in order to simplify our problem, and make our solution methods more robust, accurate and fast. In this project we will look at geometric estimation problems in computer vision, i.e. estimation of camera and 3D-geometry from image mesurements.
Where am I? This is a fundamental question we – as humans – address implicitly or explicitly most of our waking hours. We use our eyes for navigational purposes on a local scale, avoiding obstacles, finding objects etc., and on a more global scale in terms of finding our way when moving around. The localization problem, i.e. estimating the position and the orientation of a viewer or a camera given image data has attracted increasing attention over the past years. In order to solve the localization problem we need to have methods that given image data, estimates the position and orientation of the camera. We also need to relate the camera motion to some map of the environment, typically based on a 3D reconstruction.
The typical pipeline for reconstruction begins with the extraction of features from the images, with corresponding feature descriptors. The second step is an initial matching of features from different images. From these matchings the geometry is estimated, often using some robust estimation algorithm such as RANSAC. The final step is usually a non-linear refinement of the solution, so called bundle adjustment. In all the steps we have to consider both gross errors in our measurements (outliers) and errors following some error distribution (e.g. normally distributed with some standard deviation). The ability to handle massive amounts of outliers in the data is absolutely paramount. These outliers cause major problems for the non-linear optimization methods, and can often result in local minima. Another problem is the speed of convergence of the different parts of the reconstruction pipeline when the amount of input data and estimated model parameters grows very large. To remedy this, new approaches using convex optimization have been introduced in the computer vision community over the last years, see e.g. [12, 15, 17, 38].
Today cameras are ubiquitous and image data is readily available. In addition to the pure image data there is in many cases more information available both about the camera position and the structure of the scene.
Some examples are:

- Positional information of cameras, from GPS measurements.
- Positional information of cameras, from Wifi signal strength measurements.
- Depth information of world points relative camera, from cameras with depth sensors.
- Orientation information of cameras, from accelerometer measurements.
- Local velocity and motion of cameras, from gyro measurements.

a b c d

Figure 1: Comparison between SfM estimations for a city section. (a) Without using GPS cues and (b) using GPS cues. Both reconstructions are registered to a GIS model of the city section. Without using GPS information, the solution gets stuck in a local minimum. (c) The second city section without using GPS cues and (d) using GPS cues. The solution without GPS looks decent, but suffers from drift.

In many instances this additonal information is unreliable, with large amounts of noise and incomplete. However, we believe that this information should be used in conjunction with the image data in order to *simplify the estimation problem, make it more robust and make it faster*. In order to fuse data from different modalities in a consistent way, it is important to work with meaningful objective functions in the optimization as well as incorporate it in the camera motion and 3D structure models in an appropriate way.
Our overall goal is to use the additional sensor information throughout the reconstruction pipeline. We will in the preliminary work section give specific examples how this can be done. In Fig. 1 results from [36] (also described in the preliminary results section) are shown. In (b) using GPS gives better intitial estimates, avoiding local minima in the final optimization, and in (d) using GPS avoids problems with drift in the final optimization.
One of the co-applicants, Jan Erik Solem, is the founder of the crowdsourced photo mapping company Mapillary. Through Mapillary we have access to over 10 million geo-referenced images with GPS data, accelerometer and magnetometer readings.

Survey of the Field

Today there exists a number of systems that can handle very large image sets and do reconstruction from these, see e.g. [2, 7, 27]. A big problem for many of these systems is the occurrence of outliers in the data. Many approaches for robust estimation, based on the RANSAC framework, have been proposed over the years, see e.g. [5]. Another approach for handling outliers in a robust way is the L_∞-framework, see [16, 17, 30] including recent extensions [26, 37]. Many of these approaches work well for large scale problems, but break down with large rates of outliers. Solving computer vision problems using IMU or accelerometer data in addition to visual data has been proposed in a number of previous papers. Some use it together with RANSAC, [11, 19], while others use it to bootstrap the filtering process in SLAM type approaches, see [24, 28, 31, 25, 18, 33]. Many systems incorporate the positional information in the final bundle adjustment, see e.g. [20, 29, 14, 32, 21, 22]. If the initial estimates are not good enough this could lead to problems with local minima.

Project Description

We will in this section describe the type of problems that we want to solve. We will be quite general in our formulation, and we refer to the preliminary results section for a more technically detailed description of the types of approaches that we will pursue.

Incorporating additional sensor data in initial estimates

One of the most difficult problems in computer vision is the correspondence problem. This is the task of matching points in different images that are projections of the same world point, or matching points in an image to their correposponding 3D model points. Humans solve this task effortlessly, robustly and very fast. Much work has been done in order to develop good feature detectors and descriptors that help solve the matching problem [23]. However in most cases we will end up with many false matches which will be seen as outliers in the data. In many cases the outlier rate can be up to 90% i.e. we have a large majority of outliers in our data. One successful way of handling these very high amounts of outliers is the RANSAC [10] paradigm (and variations thereof). It simply fits a model to a small amount of randomly chosen data points and checks how many of the rest of the data points that fit this model. This is then repeated a number of times, and in the end we choose the best model, i.e. the model that fits as many points as possible. The main drawback of RANSAC is that the probability of picking n inliers when fitting a model using n datapoints drops dramatically as n increases, if we have a large amount of outliers in the data. This means that in order to handle large amounts of outliers we ideally want models that can be estimated using a small number of data points. This is where the additional sensor data comes in. If we have additional information on the geometry we can use this to decrease the parameter space of our models.
Another recent way of handling outliers in the data is the method described in [9]. Here it was shown how the number of outliers can be minimized in polynomial time. The theoretical result is a consequence of the theory of KKT points. The trick is to introduce a dummy goal function and then construct an algorithm for computing the complete set of KKT points to the resulting optimization problem. For the details we refer to that paper. In order for this approach to be tractable the dimension m of the parameter space should be small. Additional sensor data can be used to constrain the geometry and reduce m.
In both these settings a basic building block of the algorithm is the fitting of a model to a minimal set of data, a so called minimal problem. In computer vision these minimal problems tend to (as direct consequence of the projection equations) lead to systems of multivariate polynomial equations. So one of the main tasks is to develop fast new methods for solving specific instances of geometric computer vision problems where we have incorporated additional sensor information.

Problem 1 *Construct methods for initial estimates in computer vision problems, that are very robust to outliers and incorporate additional sensor measurements.*

Incorporating additional sensor data in optimization (bundle adjustment)

After we have found an initial estimate of our model we usually want to refine this to get the statistically correct solution given our data. Given some assumptions on the errors of the data

this can in many cases be formulated as minimizing the L_2 norm of the reprojection error with respect to the model parameters, so called bundle adjustment.
If we have additional sensor data and under the (often valid) assumption that the different types of errors are independent, it is statistically optimal to weigh the errors by their variance, see the classic paper [3].
This leads in general to problems that are not convex and minimization using gradient descent methods will lead to risks of getting stuck in local minima. In order to find a global minimum we need to have either a very good initial solution or use more sophisticated optimization methods, by relaxing the problem in some way.

Problem 2 *Construct methods for optimization in computer vision problems, that are statistically valid and that incorporate additional sensor measurements.*

Develop methodology for solving systems of polynomial equations

As stated before, solving minimal problems is an important tool in developing robust and fast algorithms for computer vision. In many cases we can design an algorithm for a specific type of polynomial system, but it would be very beneficial if we had a framework for solving a general system of polynomial equations. This is a very difficult problem. A number of methods based on algebraic geometry exist, see [4, 6]. We would like to continue the work in this direction. For polynomials with coefficients in a finite field there are efficient computer systems for generating Gröbner bases, see [8]. There are strong algebraic connections between the solution structure of a given polynomial system with coefficients in a finite field and a corresponding system with coefficients in $\mathbb{R}$. We would like to exploit these connections to construct efficient algorithms for finding the Gröbner bases of general systems of polynomial equations.

Problem 3 *Construct general methods for solving systems of polynomial equations based on algebraic geometry that are fast and numerically stable.*

Significance

The use of image data has increased dramatically over the last years, and we believe that it will continue to do so. Traditionally, images or photographs taken by people have been used as just that, images of a certain moment or event. However the use of image data for other purposes is increasing as the available data increases. The potential applications are numerous, ranging from consumer applications such as localizing yourself in a new city to health aspects such as artificial memory support for disabled persons, [13]. When moving from more technical applications to more consumer oriented applications the need for very robust systems that do not fail increases. We believe that using additional sensor information can dramatically improve these aspects of computer vision systems.

Preliminary Results

We will in this section give preliminary results on two examples, which are taken from [35, 34, 36]. We will give some of the technical results from these papers that relate to the current proposal. It should be noted however that both these examples are part of larger systems and that a number of system aspects have to be considered when designing the underlying algorithms. Due to space limitations, there is no possibility to describe these aspects here. The first example shows how knowledge of the gravitational vector can be used to simplify a system for localization from images. In the experiments the gravitational vector was given by (quite noisy) accelerometer readings available in many handheld phones and devices. We used this information for removing outliers in the data in an optimal way. This is an example of Problem 1. The second example is part of a system for large scale city 3D reconstruction. In this example we used positional cues given by GPS readings to make the optimization more robust to drift and local minima. This is an example of Problem 2. These examples will hopefully give the reader some insights both of the potential and difficulties in incorporating additional sensor information in geometric computer vision problems.

Example 1. Using orientation measurements to bootstrap outlier removal and initial estimates for localization

Our localization pipeline starts by matching SIFT features between the image and the model. We then run a fast outlier removal algorithm to quickly eliminate a large amount of wrong matches. Finally we run our minimal solvers exhaustively to find the best solution. In a number of experiments we show that this approach works for both very large models and for outlier rates up to more than 99%.

As described in [35] using the knowledge of the gravitational vector gives us a way to formulate the pose estimation problem as a special instance of a registration problem, where we want to find a planar rotation (around the gravitational vector) and a three dimensional translation. The residual constraint for a point U_i can be formulated as

$$U_i'^T E_i U_i' = 0, \quad U_i' = RU_i + t, \tag{1}$$

where E_i is given by the error cone emanating from image point i. See Fig. 2 for a depiction. We can minimize the number of outliers in polynomial time. In order to do this, we need to define a goal function on the parameter space and then construct a set of solvers that finds all the KKT points to the constructed optimization problem. The main theorem from [9] shows that one of the solution points generated in this way will be optimal with respect to the number of outliers. First we decide on a goal function f on the parameter space. Normally a linear goal function will yield the simplest equations. For $k = 1, \dots, 4$ we need to solve the following problem:

> Given a subset S of k residuals compute all points satisfying $e_i = \epsilon$ for $e_i \in S$ such that the gradients of f, the residuals in S and the embedding constraints are linearly dependent.

We will need a specialized solver for each k. One of the solution points generated in this way will be optimal with respect to the number of outliers.

For our application, each of these problems can be formulated as the solution to a system of polynomial equations. We will briefly describe how we construct the 4-Point Solver. The parameter space can be embedded in $\mathbb{R}^5$ by setting

$$R = \begin{pmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} a & -b & 0 \\ b & a & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{2}$$

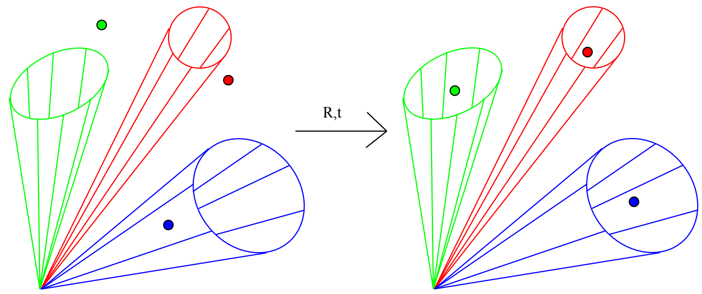

Figure 2: The registration problem for points lying on cones: Find a 3D translation and a planar rotation so that the 3D points lie on or within the error cones.

and adding the embedding constraint $a^2 + b^2 = 1$. The first four equations from (1) are in general full second degree polynomials in the five variables (a, b, t_x, t_y, t_z). Together with the embedding constraint this yields a system of five quadratic equations, which can be solved with the techniques from [4, 6]. This typically yields 28 solutions, but rarely more than 8 real-valued ones. We have implemented a fast solver where the most time consuming step is doing a QR factorization of a 280×252 matrix. On a desktop computer the running time for this type of solver is in the order of a few milliseconds.

Example 2. Using positional cues such as GPS to make robust 3D reconstructions

The reprojection error for an image point can be written as

$$r_{ij}(\theta) = \frac{\left\| \left(a_{ij}^T\theta, b_{ij}^T\theta \right) \right\|}{c_{ij}^T\theta}, \tag{3}$$

where a_{ij}, b_{ij} and c_{ij} are measured entities, and θ are the parameters we want to estimate (camera and 3D structure). The maximum likelihood solution is given by minimizing the L_2-norm of the reprojection errors, given by

$$\underset{\theta}{\text{minimize}} \sum_{i,j} r_{ij}^2(\theta). \tag{4}$$

This is not a convex problem, and only local methods exist, which cannot guarantee that the optimal solution is found. One way of handling this is to instead minimize the L_∞-norm of the errors, see [12],

$$\underset{\theta}{\text{minimize}} \ \max_{i,j} \ r_{ij}(\theta). \tag{5}$$

Using the L_∞-norm instead of the L_2-norm, makes it possible to find the global minimum. To see why, we start by rewriting the problem as

$$\underset{\theta,\epsilon}{\text{minimize}} \quad \epsilon \quad \text{s.t.} \tag{6}$$

$$r_{ij}(\theta) \le \epsilon \quad \forall\, i, j. \tag{7}$$

Here ϵ is minimized and since $\epsilon \geq r_{ij}(\theta)$ for all i and j, ϵ has to take the same value as the largest residual $\max_{i,j} r_{ij}(\theta)$. Therefore the two formulations are equivalent.
Since the depth is positive, we can use (3) to rewrite the constraints in problem (6), giving us

$$\begin{array}{c} \underset{\theta,\epsilon}{\text{minimize}} \quad \epsilon \quad \text{s.t.} \\ \left\| \left(a_{ij}^T\theta, b_{ij}^T\theta\right) \right\| \leq \epsilon\, c_{ij}^T\theta \quad \forall\, i, j. \end{array} \tag{8}$$

When ϵ and all a_{ij}, b_{ij} and c_{ij} are known these are second-order cones, and this problem can be minimized using bisection over ϵ.
In real world scenarios, incorrect point matches, i.e. outliers in the data, will prevent us from minimizing ϵ enough to get good reconstructions. We will here present a minimization scheme that can be used to remove outliers in a way similar to [30]. We start by fixing ϵ, making it a threshold for inliers. Using auxiliary variables, s_{ij} we allow the reprojection errors to become larger than the prescribed threshold ϵ. We then minimize the sum of all s_{ij} under the constraint that all $s_{ij} \geq 0$. The optimization problem becomes

$$\begin{array}{c} \underset{\theta, s_{ij}}{\text{minimize}} \quad \sum_{i,j} s_{ij} \quad \text{s.t.} \\ s_{ij} \geq 0 \\ \left\| \left(a_{ij}^T\theta, b_{ij}^T\theta\right) \right\| \leq \epsilon\, c_{ij}^T\theta + s_{ij} \quad \forall\, i, j. \end{array} \tag{9}$$

In general the global scale can never be recovered in structure from motion. In order to avoid the trivial solution $C = 0$ and $U = 0$, for all cameras and points, we fix the scale by enforcing all depths to be larger than, or equal to, 1. Note that as our formulation has a bias towards smaller reconstructions, there is no risk that the scale will increase towards infinity.
Having solved (9), all outliers can be purged from our problem by removing all image points u_{ij} for which $s_{ij} > 0$. Thus, solving one convex optimization problem, we get a solution with maximum reprojection error smaller than ϵ.
Probably the most readily available measurements, besides the image itself, is GPS-data. Thus we decided to use such information in our framework. Again the scale ambiguity produces a small problem. We require all depths to be larger than 1 and introduce an unknown scale factor on the GPS measurements. With $\hat{C}_j$ denoting a position measurement for camera j, the GPS error is

$$\frac{\left\| \varsigma\hat{C}_j - C_j \right\|}{\varsigma}, \tag{10}$$

where ς is the unknown scaling factor.
By taking camera measurements into consideration in the initial outlier removal step, the set of feasible solutions shrinks, hence, reducing the risk that an outlier fits into the solution. Although GPS measurements can be rather noisy it is uncommon with outlier measurements, so we can use hard constraints on the form $\left\| \varsigma\hat{C}_i - C_i \right\| \leq \varsigma\omega$, where ω is some predefined error threshold.
As we have seen, using a bisection algorithm, we can find the optimal solution to the L_∞ problem, but what we really want to minimize is more similar to the L_2-norm of the reprojection errors.We can formulate an approximation to the L_2-norm as a second-order cone program (SOCP). We start by looking at the squared reprojection error for one point u (dropping the indices to improve readability),

$$r^2(\theta) = \frac{\left(a^T\theta\right)^2 + \left(b^T\theta\right)^2}{(c^T\theta)^2}. \tag{11}$$

This function is non-convex and hard to optimize. Hence, we replace the denominator, with $\hat{\lambda}c^T\theta$, where $\hat{\lambda}$ is the approximative depth that we obtained from the robust reconstruction scheme proposed previously. The resulting function,

$$r^2(\theta) = \frac{\left(a^T\theta\right)^2 + \left(b^T\theta\right)^2}{\hat{\lambda}\, c^T\theta}, \tag{12}$$

can be shown to be convex.

From (10) we see that a squared GPS residual has the form $\frac{\left\|\varsigma\hat{C}_j - C_j\right\|^2}{\varsigma^2}$. Since this is the same form as the squared reprojection errors we can use the same idea to get a convex formulation. First we replace the denominator with $\hat{\varsigma}\varsigma$, where $\hat{\varsigma}$ is the approximate scale factor obtained from the initial robust reconstruction step. This gives

$$\underset{\theta, q_i, \varsigma}{\text{minimize}} \quad \sum_i q_i \quad \text{s.t.} \tag{13}$$

$$\left\| \begin{pmatrix} 2(\varsigma\hat{C}_i - C_i) \\ q_i - \hat{\varsigma}\varsigma \end{pmatrix} \right\| \leq q_i + \hat{\varsigma}\varsigma. \tag{14}$$

Note that without the depth-constraints presented earlier, this formulation does not make sense since an optimal solution is to set all variables to zero.

The results of the proposed approach on a real data-set can be seen in Fig. 1.

Equipment

As dataset for research we have access to Mapillary[1] images. This dataset is currently constituted of over 10 million geo-referenced images with GPS data, accelerometer and magnetometer readings collected from smartphones. In total these cover 300 000 km.

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[30] K. Sim and R. Hartley. Removing outliers using the L_∞-norm. In *Conf. Computer Vision and Pattern Recognition*, 2006.

[31] Bastian Steder, Giorgio Grisetti, Slawomir Grzonka, Cyrill Stachniss, Axel Rottmann, and Wolfram Burgard. Learning maps in 3d using attitude and noisy vision sensors. In *Intelligent Robots and Systems*, 2007.

[32] C. Strecha, T. Pylvanainen, and P. Fua. Dynamic and scalable large scale image reconstruction. In *Proc. Conf. Computer Vision and Pattern Recognition, Colorado springs, USA*, 2010.

[33] D. Strelow and S. Singh. Motion estimation from image and inertial measurements. *Int. Journal of Robotics Research*, 23(12):1157–1195, 2004.

[34] Linus Svärm. *Efficient Optimization Techniques for Localization and Registration of Images*. PhD thesis, Centre for Mathematical Sciences LTH, Lund University, Sweden, 2015.

[35] Linus Svärm, Olof Enqvist, Magnus Oskarsson, and Fredrik Kahl. Accurate localization and pose estimation for large 3d models. In *Conf. Computer Vision and Pattern Recognition*, 2014.

[36] Linus Svärm and Magnus Oskarsson. Structure from motion estimation with positional cues. In *Scandinavian Conf. on Image Analysis*, 2013.

[37] J. Yu, A. Eriksson, T.-J. Chin, and D. Suter. An adversarial optimization approach to efficient outlier removal. In *Int. Conf. Computer Vision*, 2011.

[38] C. Zach and M. Pollefeys. Practical methods for convex multi-view reconstruction. In *Proc. 11th European Conf. on Computer Vision, Heraklion, Greece*, 2010.

Interdisciplinarity

My application is interdisciplinary

☐

An interdisciplinary research project is defined in this call for proposals as a project that can not be completed without knowledge, methods, terminology, data and researchers from more than one of the Swedish Research Councils subject areas; Medicine and health, Natural and engineering sciences, Humanities and social sciences and Educational sciences. If your research project is interdisciplinary according to this definition, you indicate and explain this here.

Click here for more information

Scientific report

Scientific report/Account for scientific activities of previous project

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Budget and research resources

Project staff

Describe the staff that will be working in the project and the salary that is applied for in the project budget. Enter the full amount, not in thousands SEK.

Participating researchers that accept an invitation to participate in the application will be displayed automatically under Dedicated time for this project. Note that it will take a few minutes before the information is updated, and that it might be necessary for the project leader to close and reopen the form.

Dedicated time for this project

	Role in the project	Name	Percent of full time
1	Applicant	Magnus Oskarsson	25

Salaries including social fees

	Role in the project	Name	Percent of salary	2016	2017	2018	2019	Total
1	Applicant	Magnus Oskarsson	25	207,000	213,000	220,000	226,000	866,000
2	Participating researcher	Jan Erik Solem	10	83,000	85,000	88,000	90,000	346,000
3	Other personnel without doctoral degree	Doktorand	80	367,000	378,000	389,000	401,000	1,535,000
	Total			657,000	676,000	697,000	717,000	2,747,000

Other costs

Describe the other project costs for which you apply from the Swedish Research Council. Enter the full amount, not in thousands SEK.

Premises

	Type of premises	2016	2017	2018	2019	Total
1	Kontor	38,000	38,000	39,000	41,000	156,000
	Total	38,000	38,000	39,000	41,000	156,000

Running Costs

	Running Cost	Description	2016	2017	2018	2019	Total
1	Resor	Konferensresor	30,000	30,000	30,000	30,000	120,000
2	Utrustning	Datorer,kameror	20,000	20,000	20,000	20,000	80,000
	Total		50,000	50,000	50,000	50,000	200,000

Depreciation costs

Depreciation cost	Description	2016	2017	2018	2019

Total project cost

Below you can see a summary of the costs in your budget, which are the costs that you apply for from the Swedish Research Council. Indirect costs are entered separately into the table.

Under Other costs you can enter which costs, aside from the ones you apply for from the Swedish Research Council, that the project includes. Add the full amounts, not in thousands of SEK.

The subtotal plus indirect costs are the total per year that you apply for.

Total budget

Specified costs	2016	2017	2018	2019	Total, applied	Other costs	Total cost
Salaries including social fees	657,000	676,000	697,000	717,000	2,747,000		2,747,000
Running costs	50,000	50,000	50,000	50,000	200,000		200,000
Depreciation costs					0		0
Premises	38,000	38,000	39,000	41,000	156,000		156,000
Subtotal	745,000	764,000	786,000	808,000	3,103,000	0	3,103,000
Indirect costs	299,000	308,000	318,000	327,000	1,252,000		1,252,000
Total project cost	1,044,000	1,072,000	1,104,000	1,135,000	4,355,000	0	4,355,000

Explanation of the proposed budget

Briefly justify each proposed cost in the stated budget.

Explanation of the proposed budget*

Salaries

M. Oskarsson will work 25% in the project and J.E. Solem will work 10% in the project. This includes both research and supervision of a PhD student.
The main part of the project is a new PhD student. He/she will work 20% with department work, most likely teaching and 80% with PhD studies. The department currently adds an OH-cost corresponding to approximately 45% and 5.7% for offices. The cost for "lönekostnadspålägg" (incl. pension etc.) currently corresponds to 51.33% (i.e. LKP = 1:5133).
The inflation in Sweden was approximately 3% in 2011. In the budget I am assuming that the salary increases with 3% per year.

Equipment and Travel

The equipment budget is relatively thin. We plan to use some computers with large amounts of memory and several cores. Results will be disseminated in top-tier conferences and in journal publications. In the budget we have planned for such travel for the PhD student and the senior researchers.

Other funding

Describe your other project funding for the project period (applied for or granted) aside from that which you apply for from the Swedish Research Council. Write the whole sum, not thousands of SEK.

Other funding for this project

Funder	Applicant/project leader	Type of grant	Reg no or equiv.	2016	2017	2018	2019

CV

B: CV Magnus Oskarsson

Docent Magnus Oskarsson
Home address:
Tegelv. 21
227 30 Lund
Tel: 046 - 396789.

1 Higher education qualification

ECMI Postgraduate programme Mathematics for industry, the European Consortium for Mathematics in Industry, February 1 2002.
Licentiate in Engineering Centre for Mathematical Sciences, Engineering faculty, Lund University, May 3 2000, ”One-dimensional Retina Vision with Applications in Structure and Motion Estimation”. Supervisor Kalle Åström.
Master of Science Engineering Physics, 1997. Masters thesis: ”Creation and Propagation of Spiral Waves in Myocardial tissue”.

2 Doctoral degree

PhD Centre for Mathematical Sciences, Engineering faculty, Lund University, 2003, ”Solutions and their ambiguities for structure and motion problems”. Supervisor Kalle Åström.

3 Postdoctoral positions

Lund Univeristy, 40 % position at the department of cell and organism biology, 2006-2010.

4 Qualification required for appointments as a docent

LTH Docent, Lund University, 140124 to present.

5 Current position

LTH Associate professor at the Centre for Mathematical Sciences, Lund University, 090801 to present.

6 Previous positions and periods of appointment

LTH Researcher at the Centre for Mathematical Sciences, Lund University, 080101 to 090801. The position includes 40% research and 60% teaching.
LTH Assistant professor at the Centre for Mathematical Sciences, Lund University, 030101 to 071230. The position includes 75% research and 25% teaching.
LTH Temporary lecturer at the Centre for Mathematical Sciences, 2003. LTH PhD student position 970901-021230. The position includes 80% research studies and 20% teaching.

Kockums summer intern June-August 1998, Simulating electric systems for use under water. Kockums builds submarines. Sundlink Contractors summer intern July-August 1997, Doing ground investigations in Öresund. Sundlink Contractors built the bridge between Malmö, Sweden and Copenhagen, Denmark.

7 Interruption in research

Paternity leave Astrid: Paternity leave 100701-101231, Kerstin: Paternity leave 110101-110630 and Valter: Paternity leave 140901-141231

8 Supervision

Have been the main supervisor of one PhD-student: Linus Svärm.

9 Other information of relevance to the application

Supervision

Has supervised 36 masters thesis students.
Currently co-supervising two PhD-students: Has co-supervised four PhD-student: Henrik Stewénius, Klas Josephson, Erik Ask and Yubin Kuang.

Research Projects

I have participated in applying for, planning and executing research within the projects:
SSF VINST (Wearable Visual Information Systems), 2009-2014.
Vinnova Autometa (Automatisk generering, access och sökning på bildmetadata i mobila enheter), 2007-2009.
EU FP6 SMERobot, 2005-2008.
Toyota Dimlight vision. Externally financed project, 2005-2008.
VR Geometry of multi-camera platforms, 2005-2008.
SSF VISCOS 2 (Vision in cognitive systems, continuation), 2007-2008.
SSF VISCOS (Vision in cognitive systems), 2003-2006.
EU IST-2001-34405 LAVA (Learning for Adaptable Visual Assistants), 2002-2005.
VR Artificial visual systems, 2001-2002.
NDC Externally financed project for development of computer vision for autonomous guided vehicles. A product called Autosurveyor II was released in spring 1999.

Patents

2 patents.
Awards Winner of Venture cup south 2009/2010
Third place Venture cup Sweden 2009/2010
Nocturnal Vision AB (which I co-founded in 2011) received one of the Vinn Nu awards 2010.
Nocturnal Vision AB (which I co-founded in 2011) was on the Swedish Institute's list of the top 20 innovations in 2011.

Curriculum Vitae for Jan Erik Solem

March 25, 2015

Personal data:

Name: Jan Erik Solem
Date-of-birth: 28 January 1976
Nationality: Norwegian
Marital status: Married
Address: Ottars väg 4, 237 31 Bjärred

Academic degrees

2006 Ph.D. (Teknologie Doktor) in Applied Mathematics at LTH, Lund University, Sweden. Title: *Variational Problems and Level Set Methods in Computer Vision – Theory and Applications*. Advisor: Professor Anders Heyden.

2004 Tekn.Lic. (Teknologie Licentiat) in Applied Mathematics at LTH, Lund University, Sweden. Title: *Variational Surface Fitting for Computer Vision Problems*. Advisor: Professor Anders Heyden.

2001 M.Sc. (Civ. ing.) in Engineering Physics from Lund Institute of Technology, Sweden. Title: *Compression of Fingerprint Template Images*.

1995 High school degree (Gymnasieexamen) from Spyken, Lund.

Current positions

Sep 2013– CEO and Founder, Mapillary AB

Jan 2009– Associate Professor (on part time leave), Centre for Mathematical Sciences, Lund University, Sweden.

Former positions

Jan 2013–Jul 2013 Computer Vision Researcher, Apple AB, Sweden.

Oct 2010–Dec 2012 Engineering Manager, Apple Inc, Cupertino, CA, USA.

Jul 2006–Sep 2010 CTO and Founder, Polar Rose AB, MalmÃű, Sweden.

Nov 2004–Jul 2006 CEO and Founder, Polar Rose AB, MalmÃű, Sweden.

Jul 2002–Sep 2006 Ph.D.-student at the Applied Mathematics Group, School of Technology and Society, Malmö University, Sweden.

Jan 2002–Jun 2002 Research Engineer, Dept. of Mathematics, Lund Institute of Technology, Sweden.

Aug 2001–Dec 2001 Degree Thesis, Precise Biometrics AB, Lund, Sweden.

Supervision record:

Assistant PhD advisor for Fangyuan Jiang, Erik Ask, Yubin Kuang (Lund University), Christian Andersson (Malmö University).

Publication list

C: List of publications 2008-2015 Magnus Oskarsson

Publication list extracted from Mathematical Imaging Group
http://www.maths.lth.se/vision/publications/.
Citation counts from Google Scholar.
http://scholar.google.com/citations?hl=sv&user=zErxvQoAAAAJ

1 Peer-reviewed original articles

1. E. Warrant, M. Oskarsson and H. Malm, The Remarkable Visual Abilities of Nocturnal Insects: Neural Principles and Bioinspired Night-Vision Algorithms. *Proceedings of IEEE*, 102(10): 1411-1426, 2014, Number of citations: 1.

2. A. Garm, M. Oskarsson and D.E. Nilsson, Box jellyfish use terrestrial visual cues for navigation, *Current Biology*, 21:9, 798-803, 2011, Number of citations: 36.

3. C. Olsson, F. Kahl and M. Oskarsson. Branch and Bound Methods for Euclidean Registration Problems. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(5): 783-794, 2009, Number of citations: 42.

2 Peer-reviewed conference contributions

4. (*) F. Jiang, M. Oskarsson and K. Åström, On the Minimal Problems of Low-Rank Matrix Factorization, *In Proc. Computer Vision and Pattern Recognition*, Boston, USA, 2015.

5. M. Oskarsson, Democratic tone mapping using optimal K-means clustering, *In Proc. Scandinavian Conference on Image analysis*, Copenhagen, Denmark, 2015.

6. M. Oskarsson, Regularizing image intensity transformations using the Wasserstein metric, *In Proc. Scandinavian Conference on Image analysis*, Copenhagen, Denmark, 2015.

7. (*) L. Svärm, O. Enqvist, F. Kahl, and M. Oskarsson, Improving robustness for intersubject medical image registration using a feature-based approach, *In Proc. International Symposium on Biomedical Imaging*, New York, USA, 2015, Number of citations: 1.

8. R. Weegar, L. Hammarlund, A. Tegen, M. Oskarsson, K. Åström, and P. Nugues, Visual Entity Linking: A Preliminary Study, *In Proc. AAAI 2014 Workshop on Cognitive Computing for Augmented Human Intelligence*, 2014.

9. (*) L. Svärm, O. Enqvist, M. Oskarsson and F. Kahl, Accurate Localization and Pose Estimation for Large 3D Models, *In Proc. Computer Vision and Pattern Recognition*, Columbus, USA, 2014.

10. Y. Kuang, M. Oskarsson and K. Åström, Revisiting Trifocal Tensor Estimation using Lines, *ICPR 2014. 22th International Conference on Pattern Recognition*, Stockholm, Sweden, 2014.

11. A. Tegen, R. Weegar, L. Hammarlund, M. Oskarsson, F. Jiang, D. Medved, P. Nugues and K. Åström, Image Segmentation and Labeling Using Free-form Semantic Annotation, *ICPR 2014. 22th International Conference on Pattern Recognition*, Stockholm, Sweden, 2014, Number of citations: 1.

12. (*) M. Oskarsson, K. Åström and A. Torstensson, Prime Rigid Graphs and Multidimensional Scaling with Missing Data, *ICPR 2014. 22th International Conference on Pattern Recognition*, Stockholm, Sweden, 2014.

13. D. Medved, F. Jiang, P. Exner, M. Oskarsson, P. Nugues and K. Åström, Combining Text Semantics and Image Geometry to Improve Scene Interpretation, *Proceedings of ICPRAM 2014 The 3rd International Conference on Pattern Recognition Applications and Methods*, Angiers, France, 2014, Number of citations: 2.

14. (*) L. Svärm and M. Oskarsson, Structure from Motion Estimation with Positional Cues, *In Proc. Scandinavian Conference on Image Analysis*, Espoo, Finland, 2013.

15. Y. Kuang, K. Åström, L. Kopp, M. Oskarsson, Magnus and M. Byröd, Optimizing visual vocabularies using soft assignment entropies, *ACCV* 2010, Number of citations: 2.

16. C. Olsson and M. Oskarsson. A Convex Approach to Low Rank Matrix Approximation with Missing Data. *In Proc. Scandinavian Conference on Image Analysis*, Oslo Norway, 2009, Number of citations: 7.

3 Monographs

4 Research review articles

5 Books and book chapters

17. M. Oskarsson, H. Malm and E. Warrant, Nightvision, Biologically-inspired Computer Vision – Fundamentals and Applications, Wiley, 2015.

18. A. Heyden, F. Kahl, C. Olsson, M. Oskarsson, and X-C. Tai (Editors), Energy Minimization Methods in Computer Vision and Pattern Recognition: 9th International Conference, EMMCVPR Lund, Sweden, 2013.

19. E. Warrant, M. Oskarsson and H. Malm, A Night Vision Algorithm Inspired by the Visual System of a Nocturnal Bee, Biomimetics in Photonics, Taylor & Francis, 2012

20. H. Malm, M. Oskarsson and E. Warrant, Biologically inspired enhancement of dim light video, Frontiers in Sensing, Springer 2012, Number of citations: 1.

6 Patents

21. H. Malm, E. Warrant, J. Ambeck-Madsen, H. Yanagihara and M. Oskarsson. A method, an apparatus and a computer-readable medium for processing a night vision image dataset *US Patent 8,139,889, EP Patent 2,057,601, WO Patent 2,008,019,846* 2012.

List of Publications

Thesi

[1] Solem, J. E., Variational Problems and Level Set Methods in Computer Vision – Theory and Applications, *Ph.D. Thesis*, Dept of Mathematics, Lund University/LTH, 2006. **Best Nordic PhD-thesis in the field of Image Analysis and Pattern Recognition in the period 2005-2006.**

[2] Solem, J. E., Variational Surface Fitting for Computer Vision Problems, *Licentiate Thesis*, Dept of Mathematics, Lund University/LTH, 2004.

Book Chapters

[3] Fuhrer, C., Solem, J.E., Verdier, O., Computing with Python, Pearson, 2013. (ISBN-13: 978-0273786436)

[4] Solem, J.E., Programming Computer Vision with Python, O'Reilly Media, 2012. (ISBN 978-1-4493-1654-9)

[5] Overgaard, N.C., Solem, J.E., Separating Rigid Motion for Continuous Shape Evolution, *in Progress in Computer Vision and Image Analysis*, Horst Bunke et al. (Eds), World Scientific, Series in Machine Perception and Artificial Intelligence vol. 73, 2010.

[6] Solem, J. E., Overgaard, N.C., Region-Based Variational Problems and Normal Alignment – Geometric Interpretation of Descent PDEs, *in Xue-Cheng Tai, Knut-Andreas Lie, Tony F. Chan and Stanley Osher (Eds.): Image Processing Based on Partial Differential Equations*, Springer-Verlag 2007 (ISBN 978-3-540-33266-9).

Journal Papers

[7] Overgaard, N.C., Solem, J. E., Separating Rigid Motion for Continuous Shape Evolution, *Electronic Letters in Computer Vision and Image Analysis (ELCVIA); Special issue on Partial Differential Equation methods in Graphics and Vision,* Accepted for publication, 2007.

[8] Solem, J. E, Aanæs, H., Heyden, A., Variational Surface Interpolation from Sparse Point and Normal Data, *IEEE Trans. Pattern Analysis and Machine Intelligence,* volume 29, no 1, January 2007.

[9] Solem, J. E, Heyden, A., Reconstructing Open Surfaces from Image Data, *International Journal of Computer Vision,* volume 69, issue 3, September 2006.

Refereed Conferences

[10] Kuang, Y., Solem, J.E., Kahl, F., Astrom, K., Minimal Solvers for Relative Pose with a Single Unknown Radial Distortion, *in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.

[11] Jiang, F., Kuang, Y., Solem, J.E., Astrom, K., A Minimal Solution to Relative Pose with Unknown Focal Length and Radial Distortion, *in Proc. Asian Conference on Computer Vision (ACCV)*, 2014.

[12] Marcel, S., van Zwol, R., Baeza-Yates, R.A., Heckmann, O., Solem, J.E, Oomen, J., van Gageldonk, H., Gehrig, J-P, Vives, X., Sumengen, B., Media on the web, in post-production and broadcasting: the practitioner day of the ACM 2009 International Conference on Image and Video Retrieval, *in CIVR*, 2009.

[13] Netzell, K. and Solem, J.E., Efficient Image Inner Products Applied to Active Appearance Models, *in Proc. International Conference on Pattern Recognition*, 2008.

[14] Solem, J. E., Heyden, A., Variational Segmentation using Dynamical Models for Rigid Motion, *Proc. 15th Scandinavian Conference on Image Analysis,* 2007.

[15] Overgaard, N.C., Solem, J. E., The Variational Origin of Motion by Gaussian Curvature, *Proc. First International Conference on Scale Space Methods and Variational Methods in Computer Vision,* 2007.

Earlier publications at *http://www.maths.lth.se/matematiklth/personal/solem/publications.html*.

Published Patents and Applications

[16] *3D object recognition*: US8064685 (granted)

[17] *Method of computing global-to-local metrics for recognition* : US8488873 (granted)

[18] *Auto-recognition for noteworthy objects*: US8755610 (granted)

[19] *Voice-based image tagging and searching*: WO2014004536 A3, US20130346068 (application)

[20] *Method and System of Detecting Events in Image Collections*: WO2011051091A1, US20110099199 (application)

[21] *Method of Localizing Landmark Points in Images*: WO2011042371A1, US20110080402 (application)

[22] *Face feature vector construction*: WO2013095727A1, US20130155063 (application)

[23] *Image group processing and visualization*: US20140218353 (application)

[24] *Method and system for generating and labeling events in photo collections*: WO2011051091, EP2494471 (application)

[25] *Combining Multiple Image Detectors*: US20140050404 (application)

[26] *Identifying and Parameterizing Roof Types in Map Data*: US20130321392 (application)

[27] *Automatic image orientation and straightening through image analysis*: WO2014042764, US20140071308 (application)

[28] *Automatic Detection of Noteworthy Locations*: US20130300830 (application)

[29] *Presence Sensing*: US20120287035 (application)

[30] *Object Landmark Detection in Images*: US20140355821 (application)

Open Source Software

[31] **PCV**: Open source Python module for computer vision, *https://github.com/jesolem/PCV*. (main contributor)

[32] **OpenSfM**: Open Source Structure from Motion pipeline, *https://github.com/mapillary/OpenSfM*. (contributor)

[33] **geo-tools**: Collection of Python modules for working with geo data, *https://github.com/jesolem/geo-tools*. (main contributor)

CV

Name: Magnus Oskarsson	**Doctorial degree:** 2003-01-16
Birthdate: 19721024	**Academic title:** Docent
Gender: Male	**Employer:** Lunds universitet

Research education

Dissertation title (swe)		
Dissertation title (en)		
Solutions and their ambiguities for structure and motion problems		
Organisation	**Unit**	**Supervisor**
Lunds universitet, Sweden Sweden - Higher education Institutes	Matematikcentrum 107150	Kalle Åström
Subject doctors degree	**ISSN/ISBN-number**	**Date doctoral exam**
10199. Annan matematik	91-628-5461-5	2003-01-16

CV

Name: Jan Erik Solem	**Doctorial degree:** 2006-09-29
Birthdate: 19760128	**Academic title:** Doktor
Gender: Male	**Employer:** No current employer

Research education

Dissertation title (swe)

Dissertation title (en)

Variational Problems and Level Set Methods in Computer Vision - Theory and Applications

Organisation	Unit	Supervisor
Lunds universitet, Sweden Sweden - Higher education Institutes	Matematikcentrum 107150	Anders Heyden

Subject doctors degree	ISSN/ISBN-number	Date doctoral exam
10199. Annan matematik		2006-09-29

Publications

Name: Magnus Oskarsson	**Doctorial degree:** 2003-01-16
Birthdate: 19721024	**Academic title:** Docent
Gender: Male	**Employer:** Lunds universitet

Oskarsson, Magnus has not added any publications to the application.

Publications

Name: Jan Erik Solem	**Doctorial degree:** 2006-09-29
Birthdate: 19760128	**Academic title:** Doktor
Gender: Male	**Employer:** No current employer

Solem, Jan Erik has not added any publications to the application.

Register

Terms and conditions

The application must be signed by the applicant as well as the authorised representative of the administrating organisation. The representative is normally the department head of the institution where the research is to be conducted, but may in some instances be e.g. the vice-chancellor. This is specified in the call for proposals.

The signature*from the applicant*confirms that:

- the information in the application is correct and according to the instructions form the Swedish Research Council
- any additional professional activities or commercial ties have been reported to the administrating organisation, and that no conflicts have arisen that would conflict with good research practice
- that the necessary permits and approvals are in place at the start of the project e.g. regarding ethical review.

The signature *from the administrating organisation* confirms that:

- the research, employment and equipment indicated will be accommodated in the institution during the time, and to the extent, described in the application
- the institution approves the cost-estimate in the application
- the research is conducted according to Swedish legislation.

The above-mentioned points must have been discussed between the parties before the representative of the administrating organisation approves and signs the application.

Project out lines are not signed by the administrating organisation. The administrating organisation only sign the application if the project outline is accepted for step two.

Applications with an organisation as applicant is automatically signed when the application is registered.