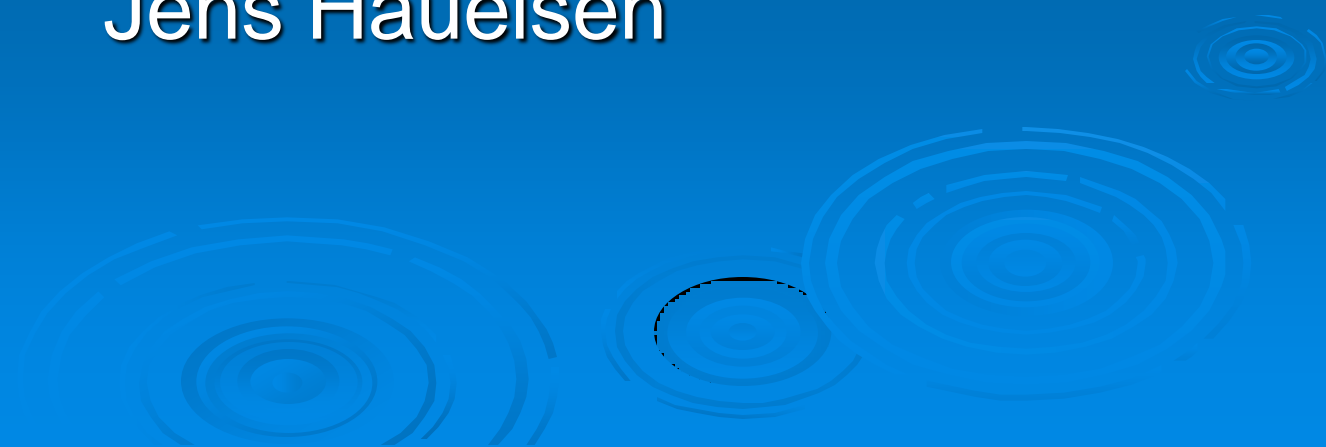


Optimization of Magnetic Sensor Systems for Magnetocardiography

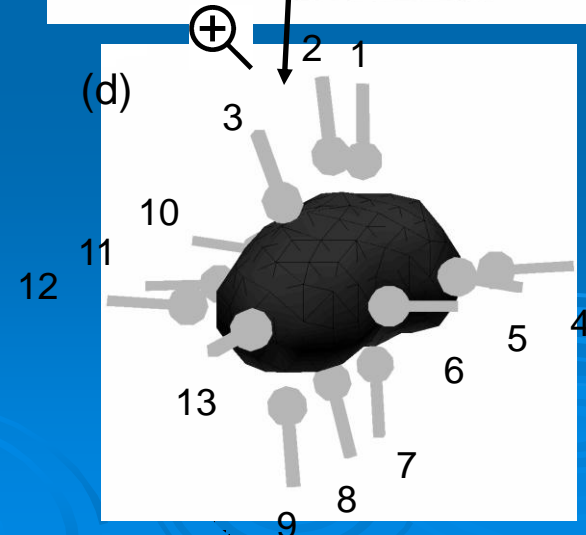
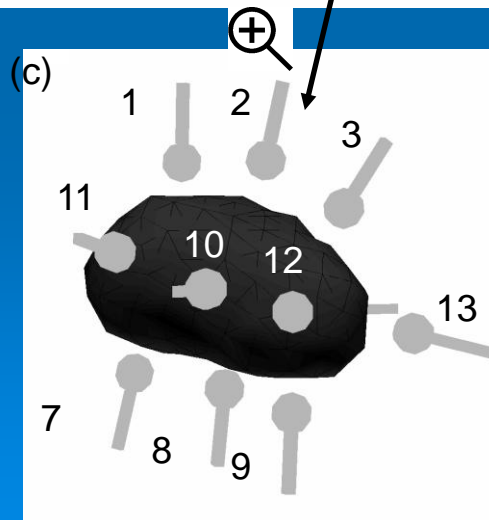
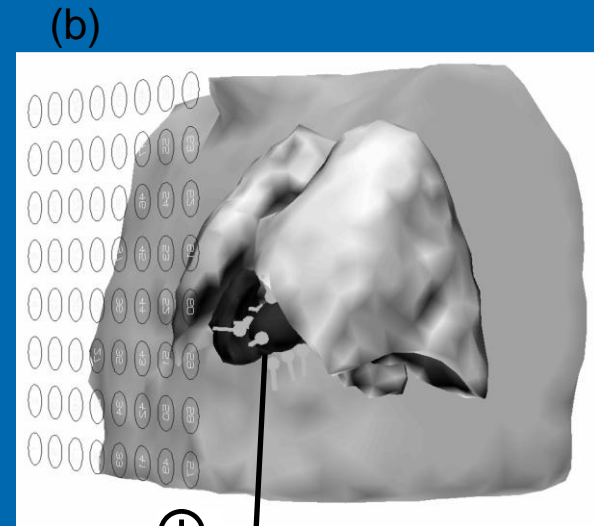
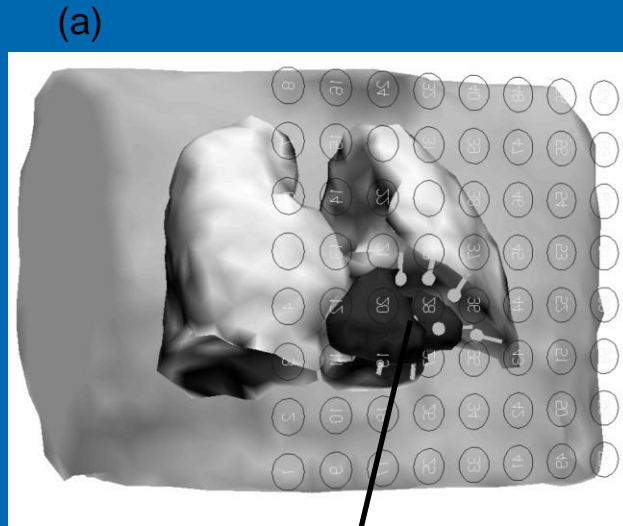
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Jens Haueisen



Introduction

- New room temperature optical magnetometers allow customized and flexible sensor arrangements
- Arising question: how do we arrange the sensors optimally?
- Goal function: condition number (CN) of the lead field (LF) matrix

Boundary element model



The objective function

- LF matrix contains information on geometry of the source space, the boundary element model (BEM) and the sensor array
- A minimal CN implies an optimal sensor arrangement for a given setup



Discretization of the search space

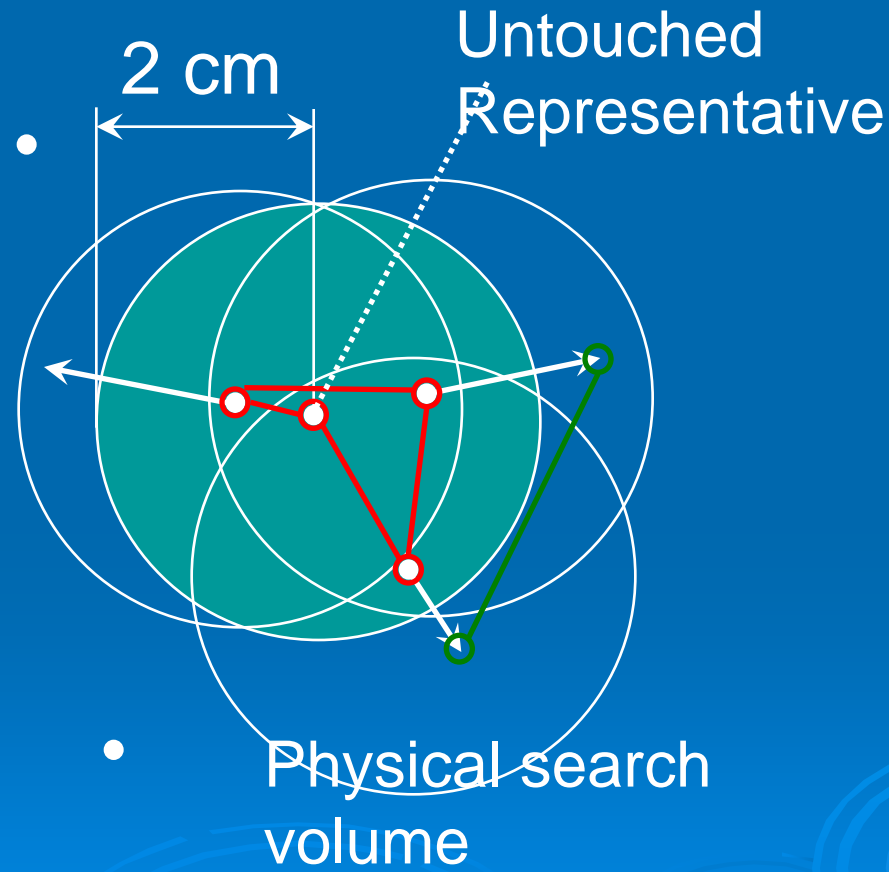
- Optimization: iterative search for a sensor setup with minimal CN
- But LF computation is slow, therefore pre-computation for a fixed grid of positions & orientations is needed



Constraint Framework for Continuous Optimizers

- Discrete search volume
→ snap into grid before each CN evaluation
- Minimum distance (MD) of sensors, here 2 cm
→ while $\text{mean}(\text{MD violation}) > \text{tolerance}$
 1. pick a sensor with max #clashes
 2. move all clashing sensors away radially
 3. snap into grid
- Pro: one representative sensor out of the clashing sensors is kept

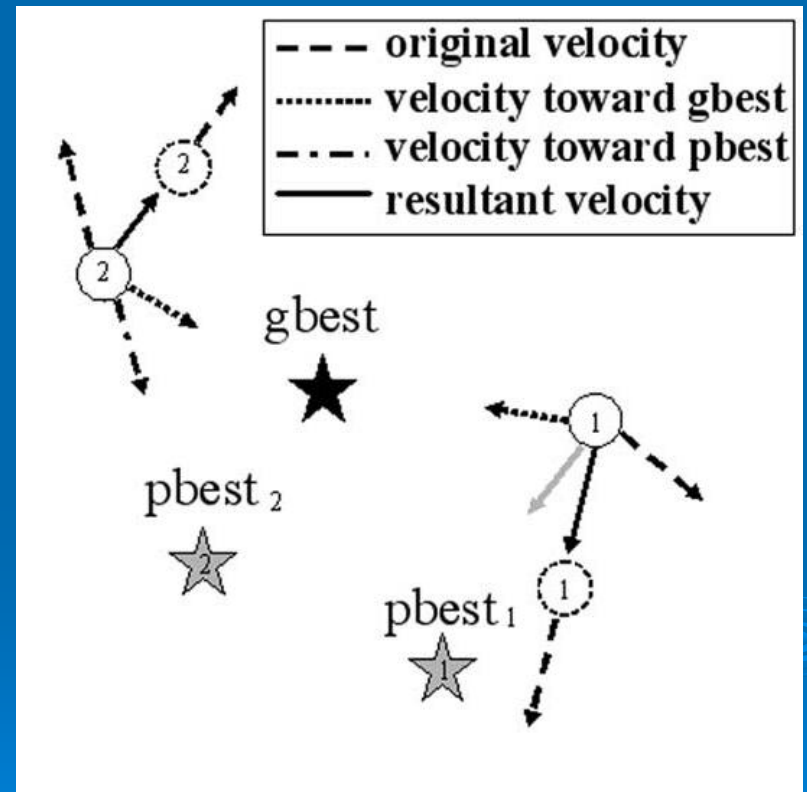
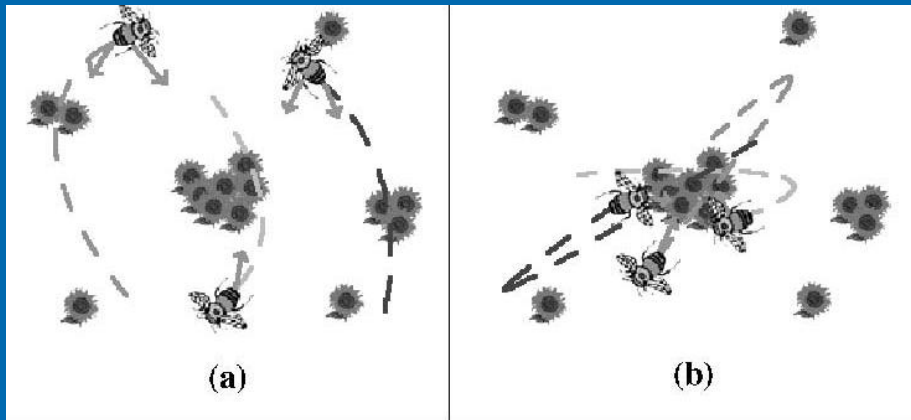
Restoring the minimum distance



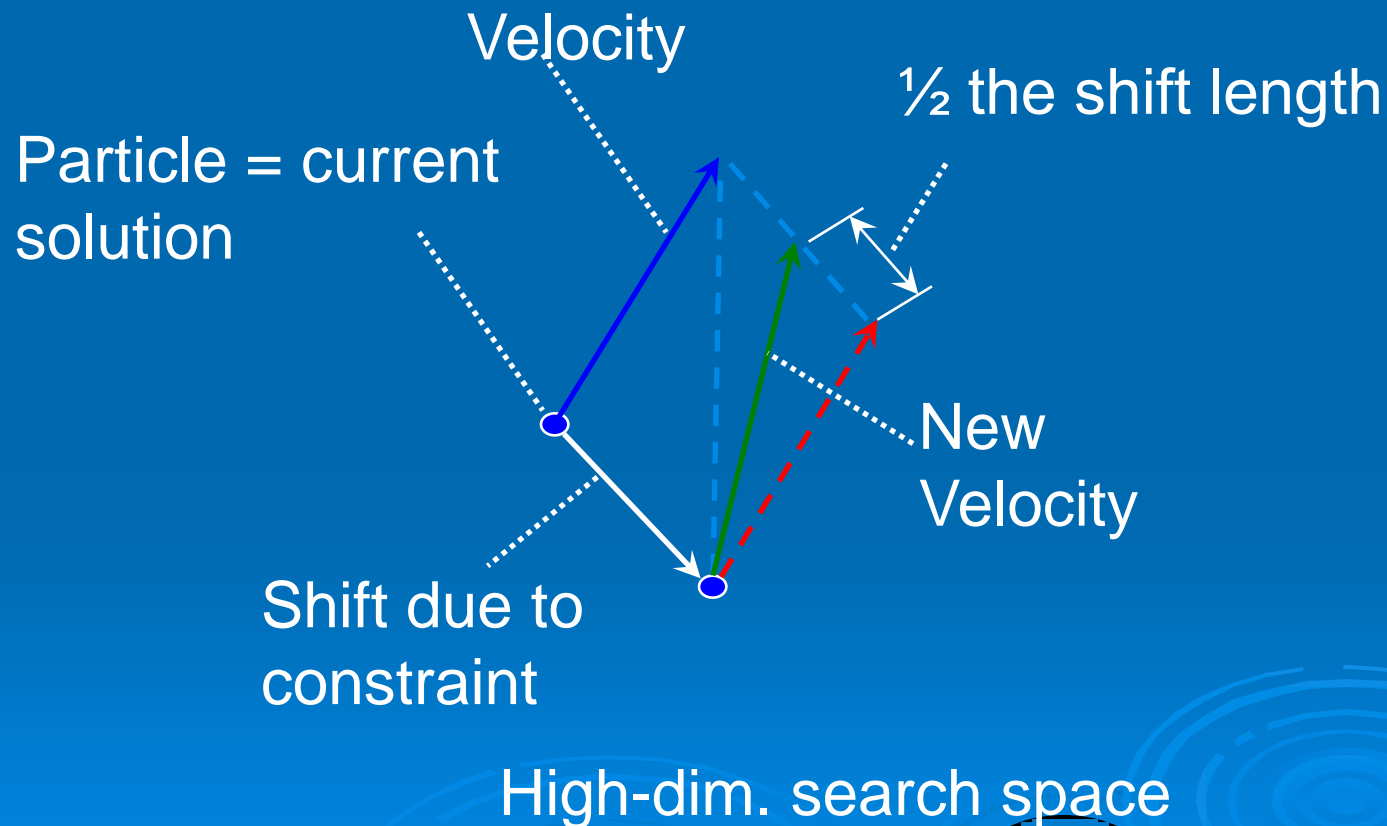
Particle Swarm Optimization (PSO)

- A set of candidate solutions (= particles) is randomly initialized
- Each particle has a position and velocity in high-dim. search space
- Each particle has informant particles, whose state it can access
- Iteration = move particles + update velocities + fix constraint
- After constraint fix, the velocities are corrected

PSO algorithm



PSO velocity correction



Tabu Search (TS)

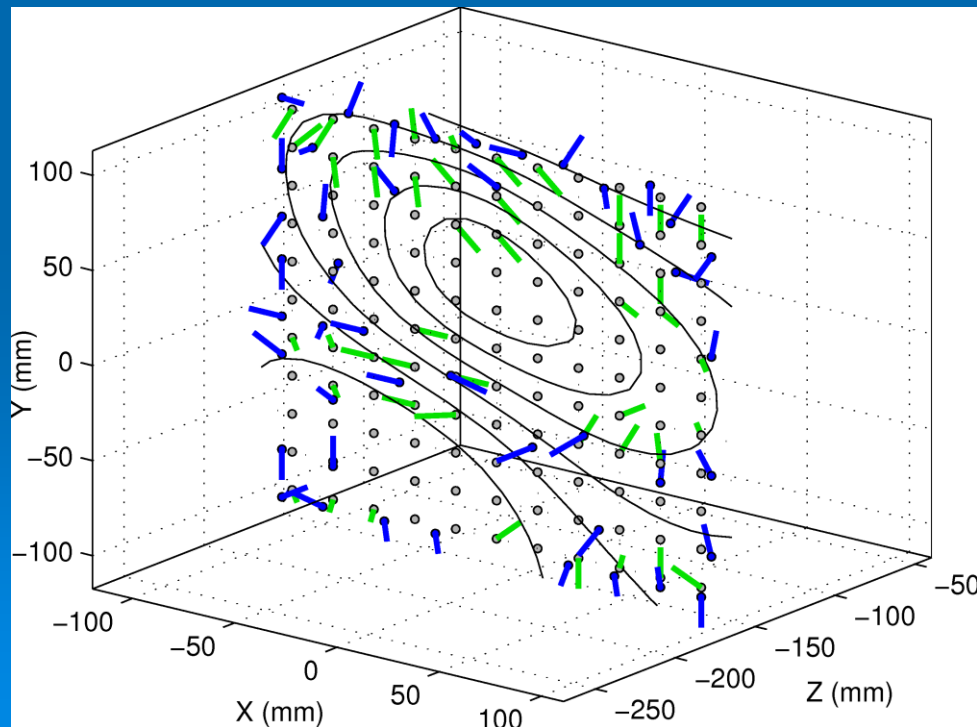
- Discrete search: combinatorial selection of s out of r sensors with minimal CN
- The minimum distance constraint is satisfied for all sensor selections
- In each iteration step: find a better selection of s sensors (with lower CN) in the neighborhood of the current solution by exchanging n sensors (during the search n was decreased from $s/2$ to 1)

PSO vs. TS

- TS prevents reevaluations of sensor configurations by memorizing them
- TS is robust against local minima
- But: no use of spatial closeness or gradient, limited to combinations of predefined sensor positions/orientations
- Dense grids (i.e. a higher number of sensors on the same area) may be more difficult to optimize than sparse ones because of the combinatorial complexity

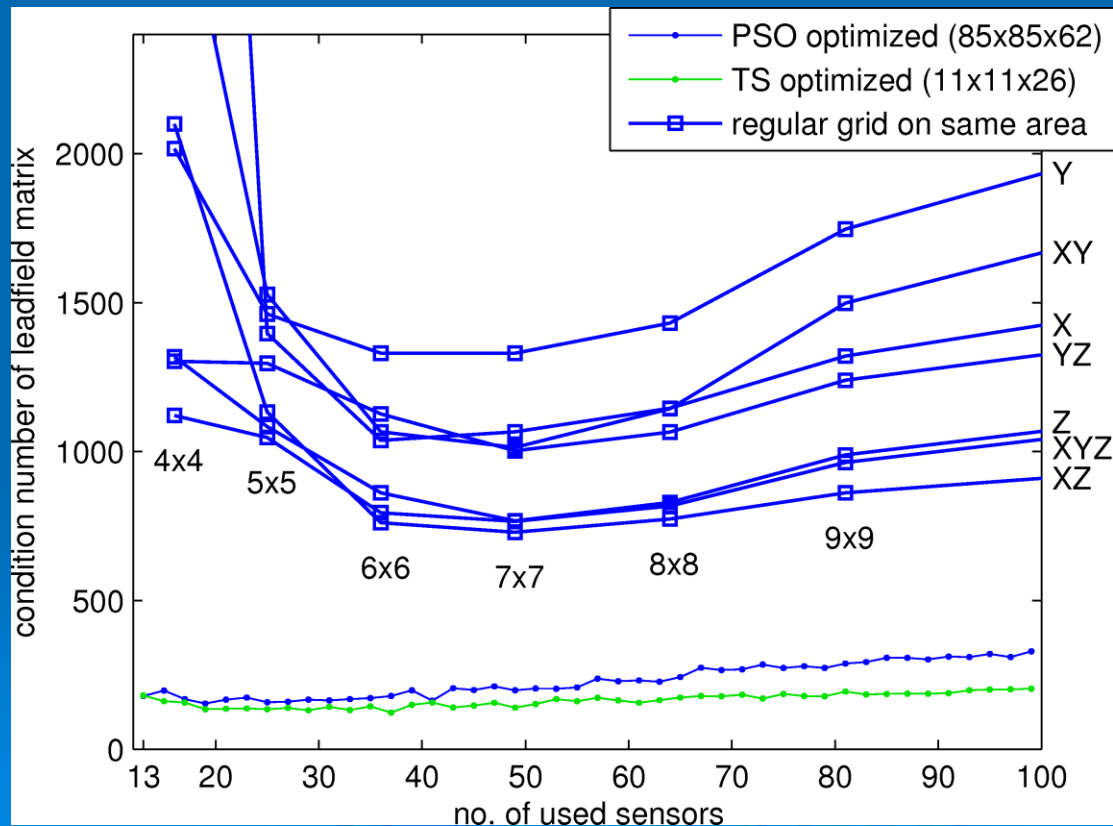
Numerical Results

- PSO and TS are implemented in C++ in SimBio: TS (green) and PSO (blue) optimized setups are very similar



Reduction of CN

- Both optimizations significantly reduce CN



Conclusion

- Comparable results indicate that optimization of vectorial sensor setups may be significantly improved
- Reconstruction robustness may be improved and the number of sensors may be reduced while retaining information in terms of CN
- The new quasi-continuous PSO optimization incorporates the gradient and spatial closeness information while being robust against local minima in the goal function
- A fine 3D search volume, projection method based and lower error bound based sensor setup optimizations are planned