SENSOR REGISTRATION IN A SENSOR NETWORK BY CONTINUOUS GRASP

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ABSTRACT. One of the main reasons in forming a sensor network is to combine the information seen from different sensors to produce a single integrated picture that is an accurate representation of the scene of interest. An often overlooked problem in network design is the proper registration of the sensors in the network. Sensor registration can be seen as the process of removing (accounting for) non-random errors, or biases, in the sensor data. Without properly accounting for these errors, the quality of the composite picture can, and oftentimes does, degrade. In this paper, we present an approach for solving the sensor registration problem, based on a new continuous meta-heuristic, when not all data is seen by all sensors, and the correspondence of data seen by the different sensors is not known *a priori*. Considering a real problem from the defense industry, we show this approach performs better than other approaches in the literature.

1. INTRODUCTION

In today's technology-driven environment, it is becoming more and more common for disparate sensors to view the same scene, or at least a partial overlap of the same scene. Military examples abound from the areas of missile defense, situation awareness, and co-operating unmanned aerial vehicles (UAVs). Medical imaging and adverse drug reaction prediction are examples of two non-military areas where more than one sensor is receiving information of the same scene. In military situations, oftentimes the data each sensor infers from the scene is passed over communication links, either directly to other sensors viewing the scene, or to a central 'processor.' Hence, these sensors form a sensor network.

In either case (sensors communicating directly, or to a central processor), with multiple views of the same scene available, there lies the ability to gain a more precise representation of the scene than any one sensor could provide alone, by combining, or 'fusing', the information each sensor infers from its view. Examples include combining kinematic track states to reduce the uncertainty of the kinematic parameters, adding an identification label to a kinematic track, and determining the number of objects of interest in the particular scene. However, it is of the utmost importance that this fusion be done correctly.

One necessary pre-requisite for fusing data from multiple views of the same scene is to remove sensor registration[1] errors. These errors come in two forms: random and systematic. The random errors arise from detection and track processing techniques [2, 3], and at the fusion stage, these errors generally cannot be reduced. On the other hand, it is imperative that systematic errors be removed before data fusion occurs. The systematic errors arise from a number of sources, namely sensor calibration offset [5], platform flexure [5],

Date: August 15, 2006.

Key words and phrases. Sensor network, sensor registration, continuous GRASP, global optimization, continuous optimization.

AT&T Labs Research Technical Report: TD-6SPSXD. To appear in *MILCOM 2006*.

[1]Sensor registration is also called data alignment, bias removal, and gridlock.

sensor perspective offset [1, 2, 15, 7, 6, 11, 13], sensor internal clock errors [7, 6], and coordinate transformations [14, 7, 1, 2, 13, 11, 6]. Sensor registration is the process by which these systematic errors are removed. Without properly accounting for these systematic registration errors, the composite representation of the scene has the potential to be less precise then any one individual sensor's view, thus defeating the purpose of a sensor network.

Algorithms for sensor registration fall into two main categories. The first class determines the systematic error assuming the association of the data across the sensors is known. Techniques for this class include least-squares estimation [2, 15, 7, 3] and Kalman filtering [5, 2]. The second class of algorithms does not assume knowledge of the data association. In effect, these types of algorithms attempt to determine the systematic error and the data correspondence at the same time [2, 1, 6, 11, 13, 10].

In this paper we present an approach to determine systematic sensor registration errors, based on a new continuous greedy randomized adaptive search procedure, C-GRASP [8]. This approach is applicable to situations where the correspondence of data between the sensors is not known *a priori*, thus falling into the second class of sensor registration algorithms. This paper is organized as follows. We begin by briefly describing the general C-GRASP algorithm, and how to apply it to the problem of sensor registration. Then, we compare our approach against two others from the literature. Finally, we provide some conclusions and future research directions.

2. C-GRASP

C-GRASP is a new meta-heuristic that was developed to solve continuous optimization problems. In [8], C-GRASP was shown to outperform several other continuous optimization heuristics on a set of standard test functions, as well as on two 'hard' real-world problems [4]. We begin by giving a short overview of the C-GRASP algorithm, and then discuss its application to sensor registration.

C-GRASP is a multi-start search procedure, with each main iteration consisting of two phases, a construction phase and a local search phase. The construction phase combines elements of greediness and randomization to form a diverse set of good-quality solutions from which to start local search. The best solution found over all iterations is kept as the final solution. Pseudo-code for the main, construction, and local search C-GRASP functions can be found in Fig. 1 to 3, and a more detailed explanation of the C-GRASP algorithm can be found in [8].

3. C-GRASP and Sensor Registration

In this section, we develop our C-GRASP algorithm for the sensor registration problem. Assume we have two sensors, A and B, and the data from sensor B has been transformed into A's coordinate system. Let N_A and N_B denote the number of targets seen by sensor A and B respectively. Without loss of generality, assume $N_A \leq N_B$. Denote by $P_A(i)$ and $C_A(i)$ the position and covariance estimates of the i^{th} track of sensor A, and similarly $P_B(j)$ and $C_B(j)$ for the j^{th} track of B. Also, there is an unknown systematic sensor registration error on the sensor B data, described by the function Ω (i.e. $\Omega(P_B(j))$, $\Omega(C_B(j))$ would remove the systematic error from the j^{th} track of sensor B). Then, the likelihood of associating the i^{th} track from sensor A with the j^{th} track of sensor B can be written as a function of Ω as

$$F_{ij}(\Omega) = \frac{1}{\sqrt{(2\pi)^m |S_{ij}|}} e^{-\frac{1}{2}\delta_{ij}^T S_{ij}^{-1} \delta_{ij}} \tag{1}$$

```
procedure C-GRASP(n, ℓ, u, f(·), MaxIters, MaxNumIterNoImprov,
                  NumTimesToRun, MaxDirToTry)
    f* ← ∞;
    for j = 1,...,NumTimesToRun do
        x ← UnifRand(ℓ, u); h ← 1;
        NumIterNoImprov ← 0;
        for Iter = 1,...,MaxIters do
            α ← UnifRand(0, 1);
            x ← Construction(x, f(·), n, h,
                             ℓ, u, α);
            x ← LocalSearch(x, f(·), n, h, ℓ, u,
                            MaxDirToTry);
            if f(x) < f* then
                x* ← x; f* ← f(x);
                NumIterNoImprov ← 0;
            else
                NumIterNoImprov ←
                    NumIterNoImprov + 1;
            end if
            if NumIterNoImprov ≥
                    MaxNumIterNoImprov then
                /* make grid more dense */
                h ← h/2;
                NumIterNoImprov ← 0;
            end if
        end for
    end for
    return(x*);
end C-GRASP;
```

FIGURE 1. Pseudo-code for C-GRASP.

where $\delta_{ij} = P_A(i) - \Omega(P_B(j))$ and $S_{ij} = C_A(i) + \Omega(C_B(j))$. We then define our objective function $F(\Omega)$ to be the negative sum over all i and j of the F_{ij} in (1). For completeness, this objective function is given in (2).

$$F(\Omega) = -\sum_{i=1}^{N_A}\sum_{j=1}^{N_B} F_{ij}(\Omega) \tag{2}$$

Our approach to the sensor registration problem can now be simply stated as:

(1) Find the Ω that minimizes (2).
(2) Apply a linear assignment algorithm to determine association between the sensor A data and the corrected sensor B data.

For the first step, we use the C-GRASP algorithm described above. For the second step, we make use of the linear assignment algorithm described in [9].

4. ALGORITHM COMPARISON

We compare our C-GRASP algorithm against the two approaches found in [1, 11] (from here on denoted as the Blackman and Levedahl algorithms, respectively). We chose the particular sensor registration application as put forth in [1, 11, 13]. Briefly, it can be described as follows. We have two sensors, one active and one passive, both viewing a scene

```
procedure Construction(x, f(·), n, h, ℓ, u, α)
    S ← {1, 2, ..., n};
    while S ≠ ∅ do
        min ← +∞; max ← −∞;
        for i = 1, ..., n do
            if i ∈ S then
                z_i ← LineSearch(x, h, i, n, f(·), ℓ, u);
                g_i ← f(z_i);
                if min > g_i then min ← g_i;
                if max < g_i then max ← g_i;
            end if
        end for
        RCL ← ∅;
        for i = 1, ..., n do
            if i ∈ S and g_i ≤ (1 − α) ∗ min + α ∗ max then
                RCL ← RCL ∪ {i};
            end if
        end for
        j ← RandomlySelectElement(RCL);
        x_j ← z_j; S ← S \ {j};
    end while
    return(x);
end Construction;
```

FIGURE 2. Pseudo-code for C-GRASP construction phase.

```
procedure LocalSearch(x, f(·), n, h, ℓ, u, MaxDirToTry)
    x* ← x; f* ← f(x); NumDirTried ← 0;
    S ← {x : ‖x* − x‖_2 = h};
    while NumDirTried < MaxDirToTry do
        NumDirTried ← NumDirTried + 1;
        x ← RandomlySelectElement(S);
        if ℓ ≤ x ≤ u then
            if f(x) < f* then
                x* ← x; f* ← f(x);
                S ← {x : ‖x* − x‖_2 = h};
                NumDirTried ← 0;
            end if
        end if
    end while
    return(x*);
end LocalSearch;
```

FIGURE 3. Pseudo-code for C-GRASP local search phase.

from possibly different perspectives. Each sensor, using no information from the other, creates tracks on the targets it senses. At some point in time, the active sensor sends its track data (state and covariance) via a communication link, to the passive sensor. The passive sensor transforms this track data into the local (i.e. passive) coordinate system. As a result of this coordinate transformation, as well as possible errors in the passive sensor perspective, systematic error is introduced into the active track data. The main component of this error is a translational shift, and other factors are small enough to be ignored. Therefore,

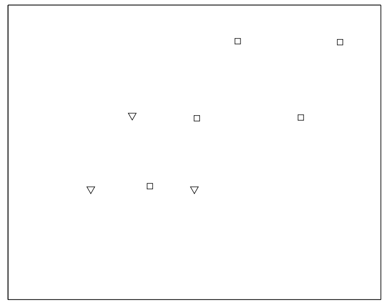

FIGURE 4. Passive sensor image plane. Triangles represent passive tracks. Squares represent active tracks. Systematic error present.

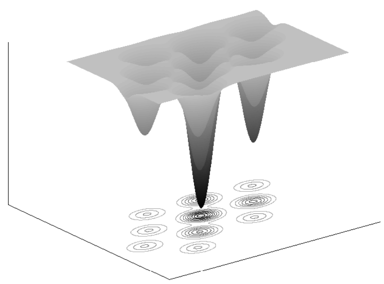

FIGURE 5. Plot of $F(\Omega)$.

for this problem, Ω defines an unknown translation, such that when Ω is applied to the active sensor data, the systematic error is removed. The goal is to correct for the translational error, and at the same time determine the association of active tracks to passive tracks. Fig. 4 shows a simple example of 3 passive tracks (triangles) and 5 active tracks (squares) when the systematic error is present (the covariances have been omitted from the figure to reduce clutter). Fig. 5 shows the $F(\Omega)$ function for this example. From this figure, you can see 10 local minimum, with only one of those being the global minimum. This global minimum gives precisely the translational error between the active and passive tracks. Finally, Fig. 6 shows the result upon running the C-GRASP algorithm to remove the systematic error; the three passive tracks align with the correct active tracks.

We briefly describe the Blackman and Levedahl approaches for this problem. The Blackman approach is an iterative scheme that starts with an initial estimate of the systematic error, applies a linear assignment algorithm (with gating) to the current corrected scene, to produce a set of assignments. From these assignments, a new estimate of the systematic error is determined. This process continues until the systematic error estimate achieves convergence (i.e. the difference between the previous and current estimate is small). The Levedahl algorithm looks at each set of possible assignments, with gating involved to limit the set of feasible assignments. For each feasible assignment vector, an

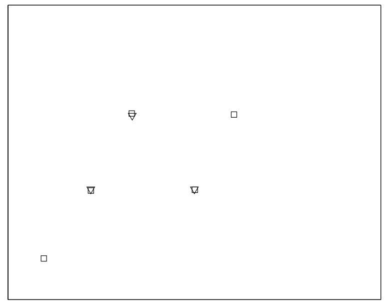

FIGURE 6. Result of C-GRASP algorithm. Systematic error removed.

estimate of the systematic error is computed. The assignment and systematic error that produces the maximum of an objective function (similar to (2)) is returned as the answer. N.B.: In the worst-case scenario, where gating does not eliminate any of the feasible assignments, the Levedahl algorithm will need to examine $\sum_{k=0}^{m} \binom{m}{k} \frac{n!}{(n-k)!}$ different assignment vectors, where m and n are the number of targets seen by the passive and active sensor, respectively.

All three algorithms were implemented by the authors in the C++ programming language and compiled with GNU `g++` version 3.2.3, using compiler options -O6 -funroll-all-loops -fomit-frame-pointer -march=i686. The algorithm used for random-number generation (needed for C-GRASP) is an implementation of the Mersenne Twister algorithm [12].

Without loss of generality, let sensor A be the passive sensor and sensor B the active sensor. Define a test class as a vector $[N_A, N_B, N_c, S_A]$, where N_A denotes the number of targets seen by sensor A, N_B denotes the number of targets seen by sensor B, N_c defines the number of targets in common to the two sensors, and S_A controls the maximum $1-\sigma$ covariance value for all targets as seen by sensor A. For each test class, we created 100 random scenarios, choosing the target positions in a square of length 20 km, and fixing the maximum $1-\sigma$ covariance value for all targets as seen by sensor B to be 3 km. After creating each scenario, we applied a random translational bias to all sensor B target data. The goal of the three algorithms is thus to determine the truthful bias, or an approximation to this bias, as well as the correct association of passive to active tracks. Table 1 lists the test classes examined in this paper. To measure the performance of the three algorithms, we looked at two metrics: the percentage of correct assignments, and the distance between each truthful correspondence. These two metrics were computed for each scenario, and averaged over each test class.

Tables 2 to 5 display the results for each test class. For each table, the first three columns show the average percentage of correct assignments for the three algorithms. Columns 4 to 6 show the average distance. The underlined number in each row of each table denote the best of the three algorithms. As is clearly seen from these tables, the C-GRASP approach does better than the other two algorithms with respect to percentage of correct assignments. For the average distance metric, the Blackman algorithm almost always performs the worst, while the Levedahl and C-GRASP approaches perform about the same.

TABLE 1. Test Classes

$\mathbf{N_A}$	$\mathbf{N_B}$	$\mathbf{N_c}$	$\mathbf{S_A}$
4	6	2	$\{0.5, 1.0, 2.0, 3.0\}$
4	6	3	$\{0.5, 1.0, 2.0, 3.0\}$
4	6	4	$\{0.5, 1.0, 2.0, 3.0\}$
5	10	2	$\{0.5, 1.0, 2.0, 3.0\}$
5	10	3	$\{0.5, 1.0, 2.0, 3.0\}$
5	10	4	$\{0.5, 1.0, 2.0, 3.0\}$
5	10	5	$\{0.5, 1.0, 2.0, 3.0\}$
7	20	2	$\{0.5, 1.0, 2.0, 3.0\}$
7	20	3	$\{0.5, 1.0, 2.0, 3.0\}$
7	20	4	$\{0.5, 1.0, 2.0, 3.0\}$
7	20	5	$\{0.5, 1.0, 2.0, 3.0\}$
7	20	6	$\{0.5, 1.0, 2.0, 3.0\}$
7	20	7	$\{0.5, 1.0, 2.0, 3.0\}$

These tables, along with knowledge of the Levedahl upper-bound on the number of possible assignments to examine, lend support to C-GRASP comparing favorably to both the Blackman and Levedahl approaches.

5. SUMMARY

In this paper, we have developed a new algorithm for the sensor registration problem. We have shown that it performs better than the approaches in [1, 11]. In addition, our approach does not suffer from the exponential worst-case performance bound of [11]. Hence, our approach can be seen as an attractive algorithm for the removal of systematic sensor registration error.

There are two areas of future research worth mentioning. First, for the particular sensor registration problem presented above, it is important to test the C-GRASP algorithm against real target geometries, not just the random scenarios. Second, in order to show the variety of problems C-GRASP can solve, work will be done to apply the C-GRASP approach to other types of sensor configurations, e.g. passive to passive, as might be evidenced by multiple UAV's viewing a scene, and active to active, which occurs when multiple active radars view the same scene.

6. ACKNOWLEDGMENT

The first author wishes to thank T. Caber and W. Foor for numerous discussions during the years $2001-2003$.

TABLE 2. $S_A = 0.5$ km

Bl	**Le**	**CG**	**Bl**	**Le**	**CG**
0.530	0.715	0.655	2.294	1.727	1.950
0.820	0.917	0.943	0.810	0.286	0.318
0.910	0.965	0.978	0.400	0.059	0.063
0.465	0.570	0.585	2.441	2.399	2.352
0.637	0.813	0.800	1.621	1.048	1.150
0.798	0.880	0.913	0.785	0.506	0.523
0.836	0.930	0.962	0.692	0.118	0.114
0.325	0.380	0.450	2.553	2.630	2.458
0.493	0.540	0.520	2.023	2.027	2.445
0.553	0.668	0.718	1.793	1.532	1.564
0.652	0.780	0.874	1.393	0.683	0.685
0.705	0.872	0.900	1.082.	0.322	0.299
0.799	0.899	0.951	0.910	0.111	0.136

TABLE 3. $S_A = 1.0$ km

Bl	**Le**	**CG**	**Bl**	**Le**	**CG**
0.625	0.770	0.785	1.826	1.336	1.305
0.793	0.880	0.927	1.043	0.798	0.497
0.945	0.960	0.993	0.282	0.061	0.092
0.450	0.650	0.615	2.607	2.090	2.297
0.677	0.853	0.833	1.450	0.802	0.901
0.820	0.923	0.943	0.826	0.348	0.342
0.856	0.948	0.972	0.677	0.058	0.024
0.375	0.345	0.430	2.342	2.760	2.510
0.483	0.617	0.653	1.995	1.778	1.548
0.573	0.755	0.757	1.783	0.946	1.003
0.594	0.802	0.826	1.488	0.724	0.732
0.745	0.863	0.952	1.026	0.381	0.298
0.747	0.920	0.987	0.995	0.095	0.096

TABLE 4. $S_A = 2.0$ km

Bl	**Le**	**CG**	**Bl**	**Le**	**CG**
0.600	0.745	0.830	1.888.	1.658	1.046
0.850	0.943	0.957	0.617	0.248	0.258
0.975	0.968	0.965	0.151	0.042	0.034
0.560	0.465	0.500	1.712	2.983	2.558
0.680	0.830	0.817	1.320	0.884	0.900
0.818	0.905	0.940	0.797	0.298	0.386
0.870	0.946	0.986	0.727	0.085	0.091
0.340	0.360	0.405	2.687	2.915	2.885
0.463	0.530	0.570	2.100	2.128	2.032
0.493	0.750	0.763	2.066	0.882	0.781
0.638	0.800	0.826	1.419	0.709	0.724
0.732	0.878	0.945	1.190	0.341	0.355
0.766	0.930	0.959	1.137	0.125	0.137

TABLE 5. $S_A = 3.0$ km

Bl	**Le**	**CG**	**Bl**	**Le**	**CG**
0.615	0.745	0.710	1.948	1.476	1.796
0.833	0.910	0.920	0.696	0.436	0.449
0.973	0.973	0.983	0.117	0.032	0.031
0.495	0.495	0.655	2.309	2.452	1.752
0.653	0.760	0.763	1.642	1.227	1.230
0.783	0.935	0.898	0.891	0.275	0.253
0.858	0.962	0.966	0.719	0.055	0.061
0.345	0.235	0.370	2.695	3.610	2.887
0.447	0.487	0.550	2.242	2.066	2.068
0.563	0.680	0.663	1.789	1.378	1.344
0.622	0.790	0.832	1.608	0.753	0.750
0.740	0.863	0.898	1.014	0.348	0.341
0.716	0.944	0.961	1.220	0.092	0.093

REFERENCES

[1] S. Blackman and N. Banh. Track association using correction bias and missing data. In O. E. Drummond, editor, *Signal and Data Processing of Small Targets (Proc. SPIE)*, volume 2235, pages 529–539, 1994.

[2] S. Blackman and R. Popoli. *Design and Analysis of Modern Tracking Systems*. Artech House, Norwood, MA, 1999.

[3] M. Dana. Registration: A prerequisite for multiple sensor tracking. In Y. Bar-Shalom, editor, *Multitarget-Multisensor Tracking: Advanced Applications*, pages 155–185. Artech House, Norwood, MA, 1990.

[4] C. A. Floudas, P. M. Pardalos, C. Adjiman, W. Esposito, Z. Gumus, S. Harding, J. Klepeis, C. Meyer, and C. Schweiger. *Handbook of Test Problems in Local and Global Optimization*. Kluwer Academic Publishers, Dordrecht, The Netherlands, 1999.

[5] R. E. Helmick and T. R. Rice. Alignment of a 2-d sensor and a 3-d radar. In *Acquisition, Tracking, and Pointing VI (Proc. SPIE)*, volume 1697, pages 142–157, 1992.

[6] M. J. Hirsch. A novel, generalized gridlock correction algorithm. In *Proc. National Fire Control Symposium*, Lihue, HI, August9–12 2004.

[7] M. J. Hirsch, W. Barker, B. Blyth, Y. Chen., R. P. DeLong, and C. Eck. Advanced techniques in track identification and correlation. In *Proc. National Fire Control Symposium*, Lihue, HI, August9–12 2004.

[8] M. J. Hirsch, C. N. Meneses, P. M. Pardalos, and M. G. C. Resende. Global optimization by continuous GRASP. *Optimization Letters*, submitted for publication (Also AT&T Technical Report TD-6MPUV9, Florham Park, NJ, March 2006.).

[9] R. Jonker and A. Volgenant. A shortest augmenting path algorithm for dense and sparse linear assignment problems. *Computing*, 39:325–340, 1987.

[10] R. Kenefic. Local and remote track file registration using minimum description length. 29(3):651–655, 1993.

[11] M. Levedahl. An explicit pattern matching assignment algorithm. In O. E. Drummond, editor, *Signal and Data Processing of Small Targets (Proc. SPIE)*, volume 4728, pages 461–469, 2002.

[12] M. Matsumoto and T. Nishimura. Mersenne twister: A 623-dimensionally equidistributed uniform pseudo-random number generator. *ACM Transactions on Modeling and Computer Simulation*, 8(1):3–30, 1998.

[13] D. Maurer. Efficient Radar-to-IR bias estimation and correlation. In *Proc. 11^{th} AIAA/MDA Technology Conference*, 2002.

[14] M. D. Miller and O. E. Drummond. Coordinate transformation bias in target tracking. In O. E. Drummond, editor, *Signal and Data Processing of Small Targets (Proc. SPIE)*, volume 3809, pages 409–424, 1999.

[15] J. J. Sudano. A least square algorithm with covariance weighting for computing the translational and rotational errors between two radar sites. In *IEEE Aerospace and Electronics Conference (NAECOM 93)*, volume 1, pages 383–387, 1993.

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