



---

# Implementing the Matrix Exponential Function on Embedded Processors

**James Lebak**

**Andrea Wadell**

**Massachusetts Institute of Technology  
Lincoln Laboratory**

**Eighth Annual High-Performance Embedded  
Computing Workshop (HPEC 2004)  
30 Sep 2004**

**This work is sponsored by the United States Navy under Air Force Contract F19628-00-C-0002. Opinions,  
interpretations, conclusions, and recommendations are those of the authors and are not necessarily endorsed by  
the United States Government.**



# Definition

[Moler and Van Loan, 2003]

---

The solution to the differential equation

$$\dot{x} = Ax(t)$$

$$x(0) = x_0$$

is given by

$$x(t) = e^{At} x_0$$

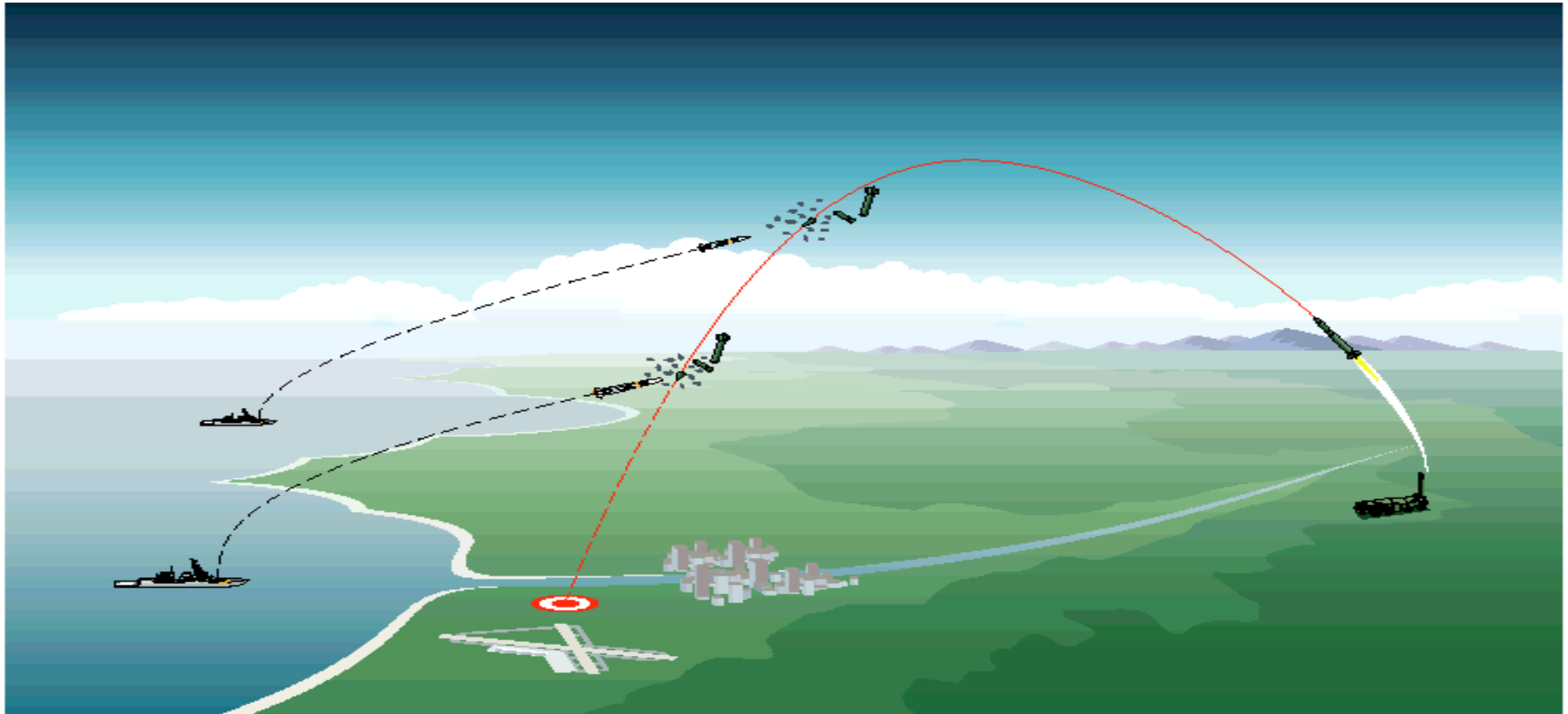
Where  $e^{At}$  is the matrix exponential function,

$$e^{At} = I + At + \frac{A^2 t^2}{2!} + \dots$$

Notice that if  $A = [a_{ij}]$ ,  $e^{At} \neq [e^{a_{ij}t}]$  in general.



# Application: Ballistic Target Tracking

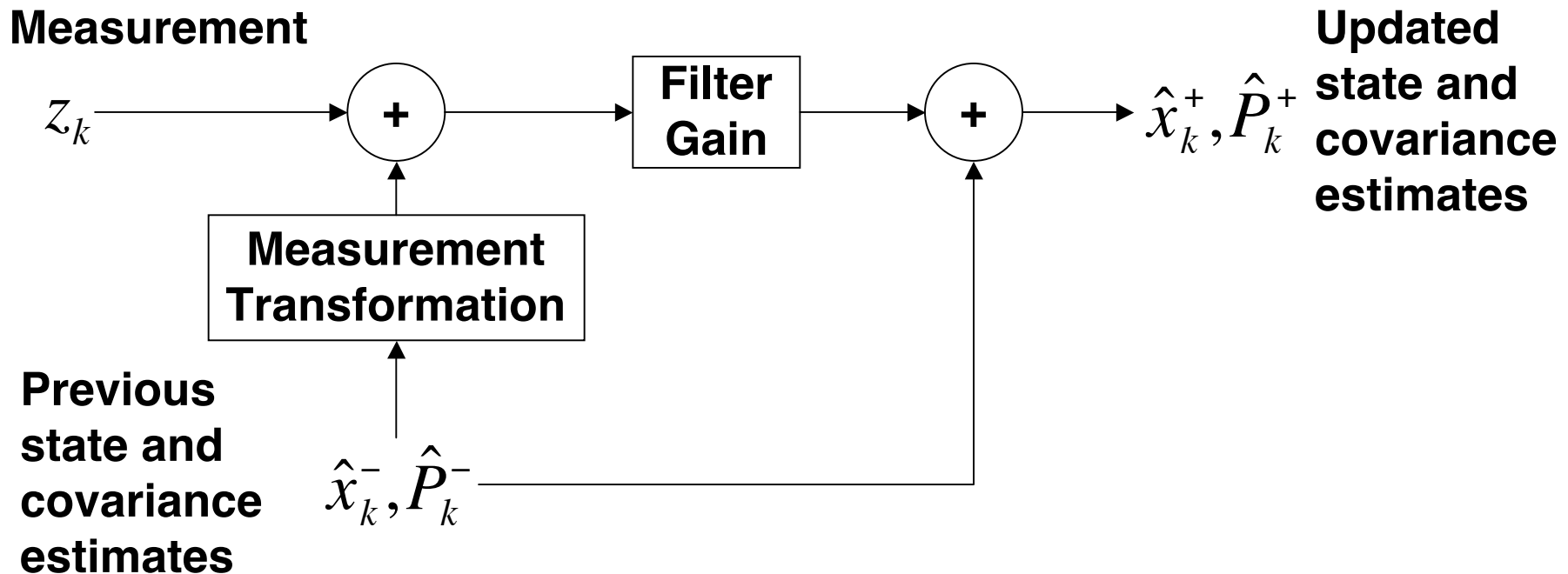


- Tracking of a ballistic target using noisy measurements
- Tracking accomplished using the *extended Kalman filter*
  - “extended” means that system dynamics are non-linear



# The Extended Kalman Filter

Estimate next state based on previous state and new measurement



$$\hat{P}_k^+ = \Phi \hat{P}_k^- \Phi + Q(t),$$

where  $\Phi = e^{Jt}$  for a matrix  $J$ ,

and  $Q(t)$  is the process noise covariance.



# Calculation Overview

**Preferred method, Padé approximation, is only valid when  $\|A\|$  is small**

**Use the fact that  $e^A = (e^{A/m})^m$**

- 1. Choose an integer  $j$  and scale  $A$  by  $m=2^j$**
- 2. Use a Padé approximation to calculate  $E = e^{A/2^j}$**
- 3. Perform  $j$  matrix multiplies to calculate  $E^{2^j}$**

**This technique is referred to as “scaling and squaring” [4,5].**



# Padé Iteration Algorithm

```
X = A;
c = 1;
E = I;
D = I;
for(k = 1; k <= q; k++) // q=number of iterations
{
    c = c * (q-k+1) / (k*(2*q-k+1));
    X = A*X;           // Matrix multiply
    E = E + cX;        // Matrix scale and add
    if (k is even)    // Matrix add or subtract
        D = D + cX;
    else
        D = D - cX;
}
E = D\E;              // Solve using LU factorization
```



# Implementation Overview

Step	Operations	Percentage of op count
Scale the matrix $A$	Elementwise multiply	<2%
Padé iteration	Matrix multiply, scale, add	50-75%
LU and backsolve		3-6%
Repeated squaring	Matrix multiply	13-50%

## Implementation Features

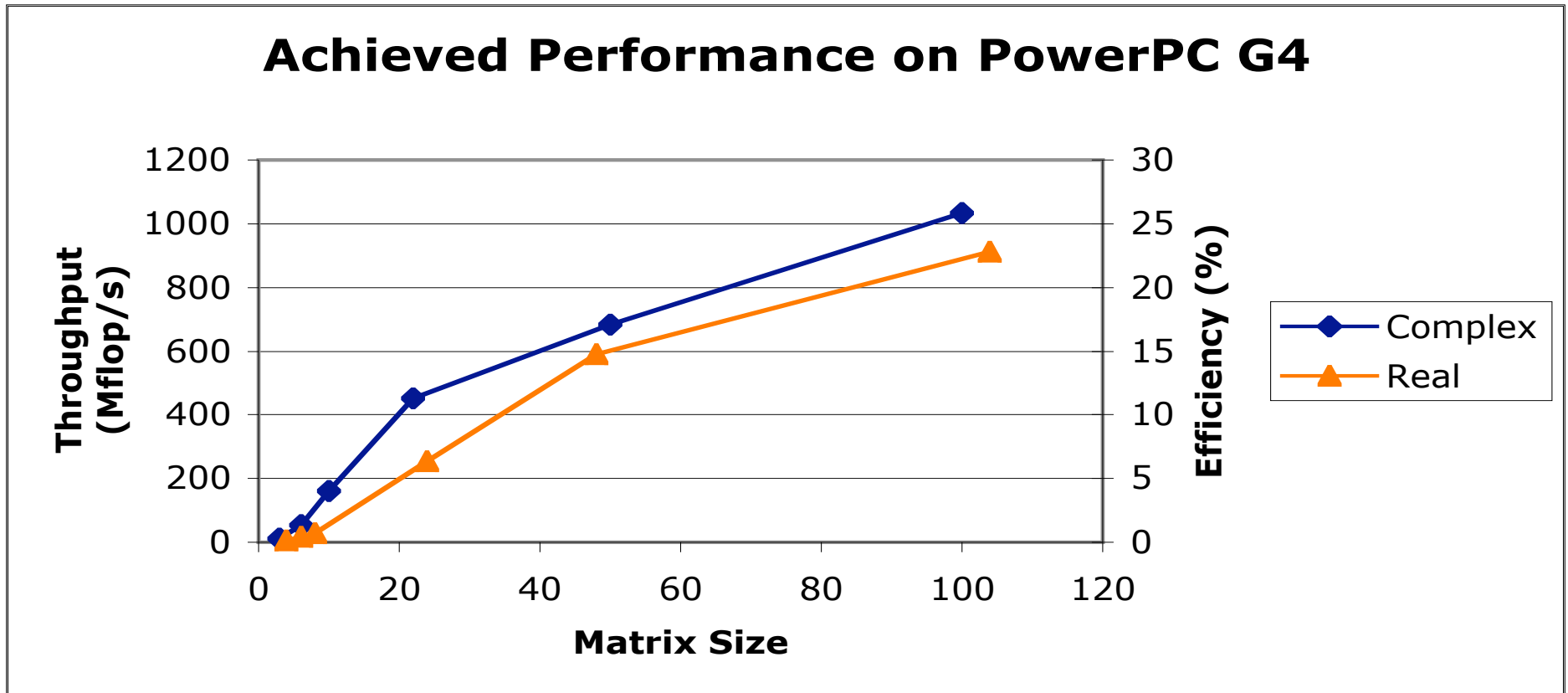
- Single-precision real or complex float
- C++
- Uses an object for storage
- Calls VSIPPL routines
- Uses Altivec-optimized matrix multiply
- Choose accuracy to match limits of single-precision calculations

Op counts assume 6 Padé iterations

```
void create(Matrix<T> &A,  
           Matrix<T> &E);  
// Allocates memory & initializes  
// LU factorization  
void run(  Matrix<T> &A,  
         Matrix<T> &E);  
// Performs computation
```



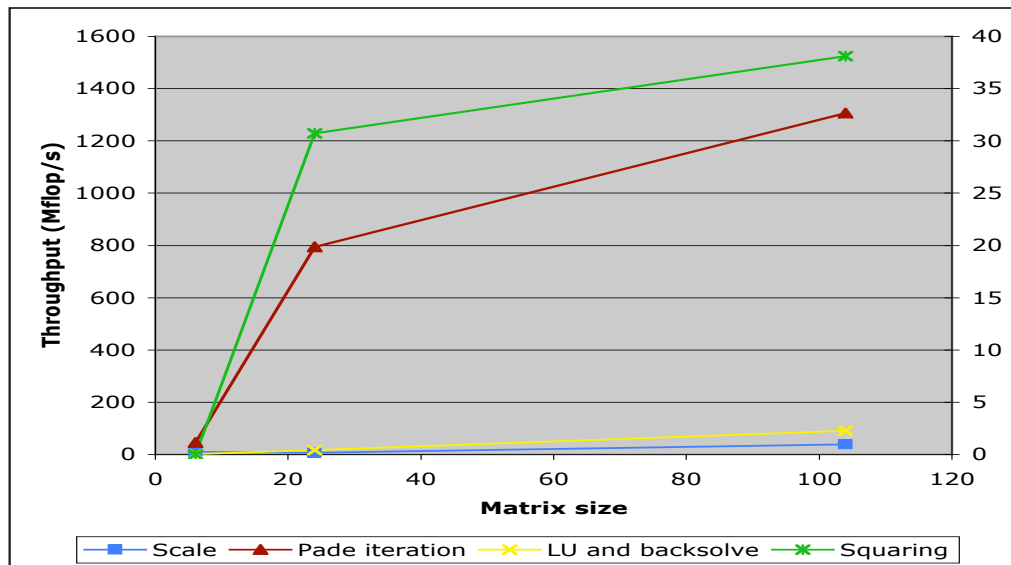
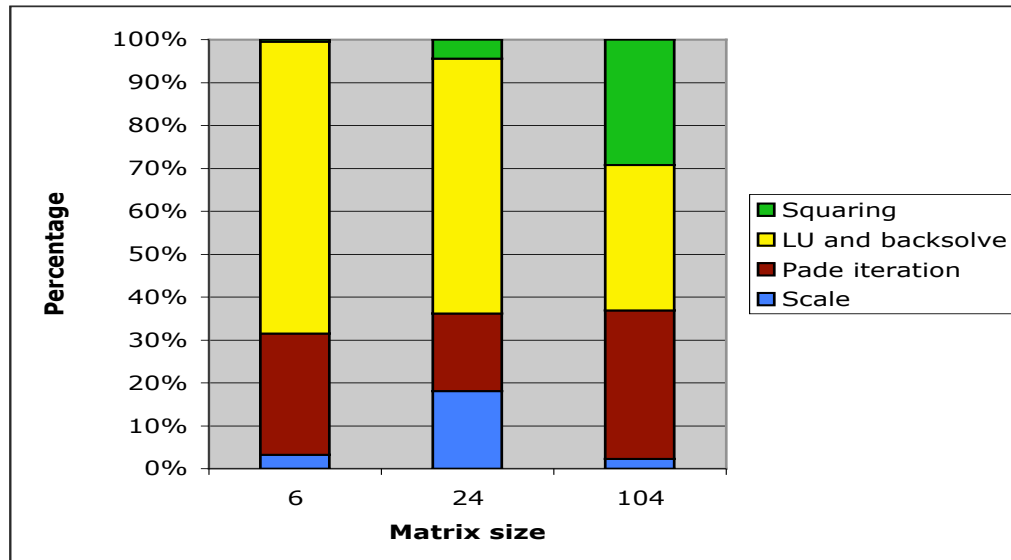
# Performance



- Platform: Mercury 500 MHz PowerPC G4
- Achieves respectable performance for large matrices
- For tracking, sizes of interest are small – 6x6 matrices
  - A tuned implementation could be produced for this size



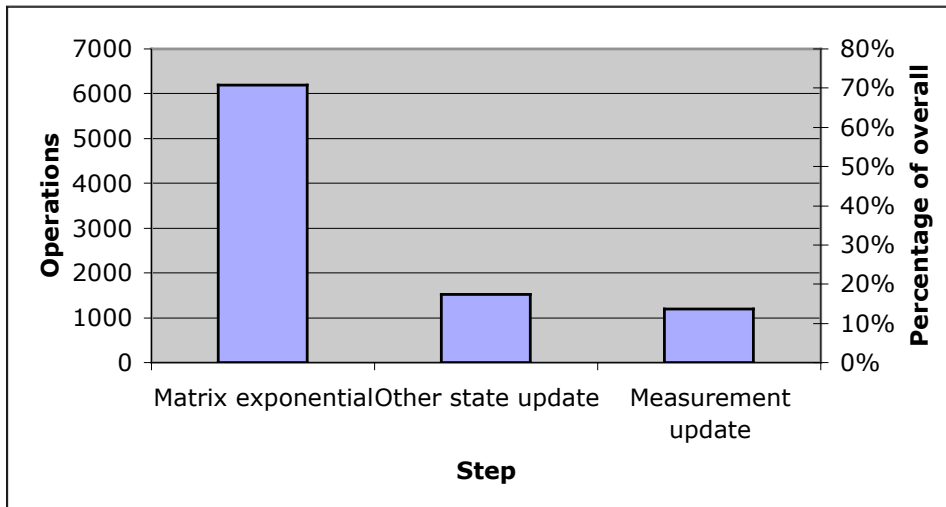
# Performance Breakdown



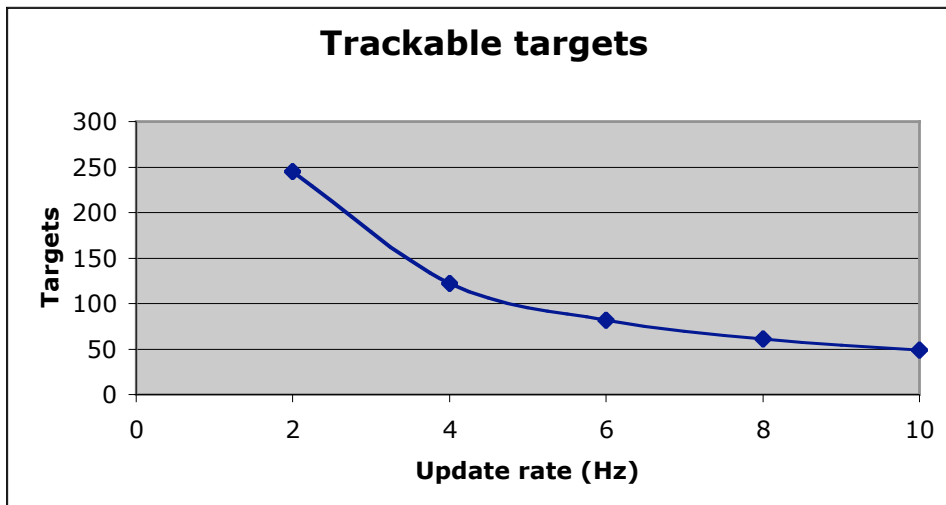
- Performance breakdown on PowerPC G4
- Steps based on matrix multiply are more efficient than other steps
- For large matrices, matrix multiply steps still consume most of the execution time
- LU/backsolve is a substantial percentage of time despite being a low percentage of the op count



# The Matrix Exponential in Tracking



- **Matrix exponential is a substantial part of the EKF's operation count**
- **How many targets could a single processor track?**
  - Assume 500 MHz PPC G4
  - Use execution time of 6x6 real matrix exponential
  - Assume remainder of EKF has efficiency comparable to LU factorization (~0.04%)
  - Vary track rate from 2-10 Hz
- **A single processor can potentially track many targets**





# Conclusions

---

- **Matrix exponential function is important for tracking applications**
- **A large percentage of the operations are matrix multiply functions**
- **An efficient implementation of this function allows it to be used in an extended Kalman filter**
- **Many targets can be tracked using even a single processor**
  - **Using multiple processors obviously allows more targets to be tracked**



# References

---

- [1] Michael Athans, Robert H. Whiting, and Michael Gruber. A suboptimal estimation algorithm with probabilistic editing for false measurements with applications to target tracking with wake phenomena. *IEEE Transactions on Automatic Control*, 22(3):372–384, June 1977.
- [2] Y. Bar-Shalom, X. Li, and T. Kirubarajan. *Estimation with Applications to Tracking and Navigation*. John Wiley and Sons, 2001.
- [3] A. Farina, B. Ristic, and D. Benvenuti. Tracking a ballistic target: comparison of several nonlinear filters. *IEEE Transactions on Aerospace and Electronic Systems*, 38(3):854–867, July 2002.
- [4] Gene H. Golub and Charles F. Van Loan. *Matrix Computations*. Johns Hopkins University Press, 3rd edition, 1996.
- [5] Cleve Moler and Charles Van Loan. Nineteen dubious ways to compute the exponential of a matrix, twenty-five years later. *SIAM Review*, 45(1):3–49, March 2003.
- [6] B. Ristic, A. Farina, D. Benvenuti and M. S. Arulampalam. Performance bounds and comparison of nonlinear filters for tracking a ballistic object on re-entry. *IEE Proceedings on Radar and Sonar Navigation*, 150(2):65–70, April 2003.