

Control and Optimization 2023/2024 (2nd semester)



Master in Electrical and Computer Engineering

Department of Electrical and Computer Engineering

A. Pedro Aguiar (pedro.aguiar@fe.up.pt), M. Rosário Pinho (mrpinho@fe.up.pt)

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Notebook #05: Stability of Nonautonomous Systems and convergence to limit cycles

1 - Nonautonomous Systems

Consider the following nonautonomous system with a limit cycle:

$$\dot{x} = -x - e^{-2t}y$$

$$\dot{y} = x - y$$

1.1

Simulate this system.

```
In [ ]: #to complete
import numpy as np
from scipy.integrate import odeint

def system(z, t):
    x, y = z[0], z[1]
    dxdt = #to complete
    dydt = #to complete
    return [dxdt, dydt]

t = np.linspace(0, 10, 1000)
z0 = [1, 1]

sol = odeint(system, z0, t)
x, y = sol[:, 0], sol[:, 1]

#plot
import matplotlib.pyplot as plt
```

```
In [5]: #Solution
import numpy as np
from scipy.integrate import odeint

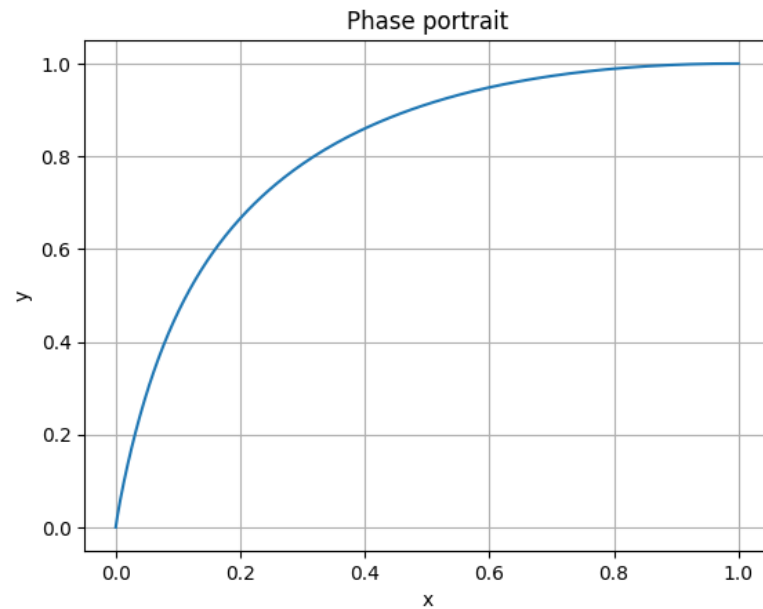
def system(z, t):
    x, y = z[0], z[1]
    dxdt = -x - np.exp(-2*t)*y
    dydt = x - y
    return [dxdt, dydt]

t = np.linspace(0, 10, 1000)
#t = np.linspace(-1, 9, 1000)
z0 = [1, 1]

sol = odeint(system, z0, t)
x, y = sol[:, 0], sol[:, 1]

import matplotlib.pyplot as plt

plt.plot(x, y)
plt.xlabel('x')
plt.ylabel('y')
plt.grid()
plt.title('Phase portrait')
plt.show()
```



1.2

To show that the origin is GUAS, we can use a Lyapunov theory for nonautonomous systems. Consider the function

$$V(t, x, y) = x^2 + (1 + e^{-2t})y^2.$$

Plot the functions $t \rightarrow V(t, x(t), y(t))$ and $t \rightarrow \dot{V}(t, x(t), y(t))$ for the trajectories already computed.

```
In [ ]: # to complete

def fV(t,x,y):
    return x*x + (1 + np.exp(-2*t)) * y

def dV(t,x,y):
    return # to complete

fV_t=fV(t,x,y)
dV_t=dV(t,x,y)

plt.plot(t, fV_t, 'r-', label='$V(t,x_t,y_t)$')
plt.plot(t, dV_t, 'b-', label='$\dot{V}(t,x_t,y_t)$')
plt.xlabel('t')
plt.title('Lyapunov function evolution')
plt.legend(loc='best')
plt.show()

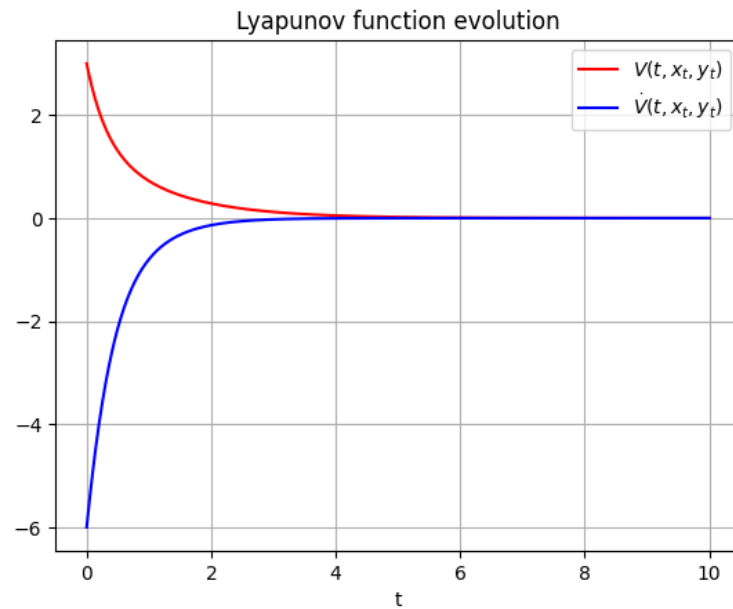
In [6]: #Solution

def fV(t,x,y):
    return x*x + (1 + np.exp(-2*t)) * y

def dV(t,x,y):
    return -2 * (x*x - x*y + y*y * (1 + 2*np.exp(-2*t)) )

fV_t=fV(t,x,y)
dV_t=dV(t,x,y)

plt.plot(t, fV_t, 'r-', label='$V(t,x_t,y_t)$')
plt.plot(t, dV_t, 'b-', label='$\dot{V}(t,x_t,y_t)$')
plt.xlabel('t')
plt.title('Lyapunov function evolution')
plt.legend(loc='best')
plt.grid()
plt.show()
```



1.3

What can you say about the stability of this system?

2- Satellite in planar orbit: convergence to a circular orbit

The equations of motion of a satellite in a planar orbit about a point mass M are:

$$\ddot{r} = r\dot{\theta}^2 - \frac{\mu}{r^2} + T \sin \phi$$

$$\ddot{\theta} = -\frac{2\dot{r}\dot{\theta}}{r} + \frac{T}{r} \cos \phi$$

where:

r = radial distance from mass M \ θ = angle from a fixed reference point in the orbit \ μ = GM, the gravitational constant of the attracting mass M \ and the control inputs are: T = thrust ϕ = thrust angle.

Take the state as $x = [r \ \dot{r} \ \theta \ \dot{\theta}]^T$, and the control input vector as $u = [\phi \ T]^T$.

Activity 1

2.1

Write the system in state space form

Solution

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= x_1 x_4^2 - \frac{\mu}{x_1^2} + u_2 \sin u_1 \\ \dot{x}_3 &= x_4 \\ \dot{x}_4 &= -\frac{2x_2 x_4}{x_1} + \frac{u_2}{x_1} \cos u_1\end{aligned}$$

2.2

One solution of the satellite equations is a circular orbit, which has values of: $r = r_0, \dot{r} = 0, \dot{\theta} = w, T = 0$ and $\mu = r_0^3 w^2$ (this is Kepler's third law). The constant angular velocity is equal to w , and the constant radius of the circular orbit is r_0 . Assume that the thrust angle is 90 degrees at nominal.

Simulate the nominal trajectory x_0 and small perturbations around it.

```

In [ ]: # To complete

import numpy as np
from scipy import integrate
import matplotlib.pyplot as plt
# show plots in notebook
# matplotlib inline

# parameters
r0=2
w=6
mu=(r0**3) * (w**2)

# vector field
def Sys_f(x, t=0):
    r=x[0]
    dr=x[1]
    th=x[2]
    dth=x[3]
    dx1= ...
    dx2= ...
    dx3= ...
    dx4= ...
    return np.array([ dx1, dx2, dx3, dx4
                      ])

# generate 1000 linearly spaced points for t
t_end=10
t = np.linspace(0, t_end, 1000)

# initial values:
x0 = np.array([r0, 0.0, 0, w])
#x0 = np.array([r0+0.2, 0.0, 0, w])

# integrate.odeint
x = integrate.odeint(Sys_f, x0, t, full_output=False)

x1,x2, x3, x4 = x.T

#plot

plt.figure(1)
plt.plot(t, x1, 'k-', label='$r$')
plt.plot(t, x2, 'b-', label='$dr$')
#plt.plot(t, x3*360/6.28, 'g-', label='$\theta$')
plt.plot(t, x4, 'r-', label='$d \theta$')
plt.title("Satellite Dynamics in time")
plt.xlabel("time")
plt.grid()
plt.legend(loc='best')

plt.figure(2)
# setting the axes projection as polar
plt.axes(projection = 'polar')
plt.polar(x3, x1, 'r-')

```

```

In [12]: # Solution

import numpy as np
from scipy import integrate
import matplotlib.pyplot as plt
# show plots in notebook
# matplotlib inline

# parameters
r0=2
w=6
mu=(r0**3) * (w**2)

# vector field
def Sys_f(x, t=0):
    r=x[0]
    dr=x[1]
    th=x[2]
    dth=x[3]
    dx1=dr
    dx2= r * (dth*dth) - mu/(r*r)
    dx3=dth
    dx4= - 2 * dr * dth /r
    return np.array([ dx1, dx2, dx3, dx4
                      ])

# generate 1000 linearly spaced points for t
t_end=10
t = np.linspace(0, t_end, 1000)

# initial values:
x0 = np.array([r0, 0.0, 0, w])
#x0 = np.array([r0+0.2, 0.0, 0, w])

# integrate.odeint
x = integrate.odeint(Sys_f, x0, t, full_output=False)

x1,x2, x3, x4 = x.T

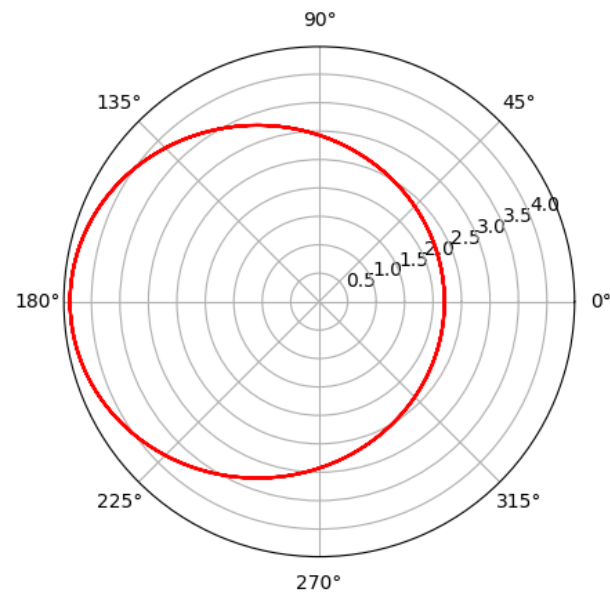
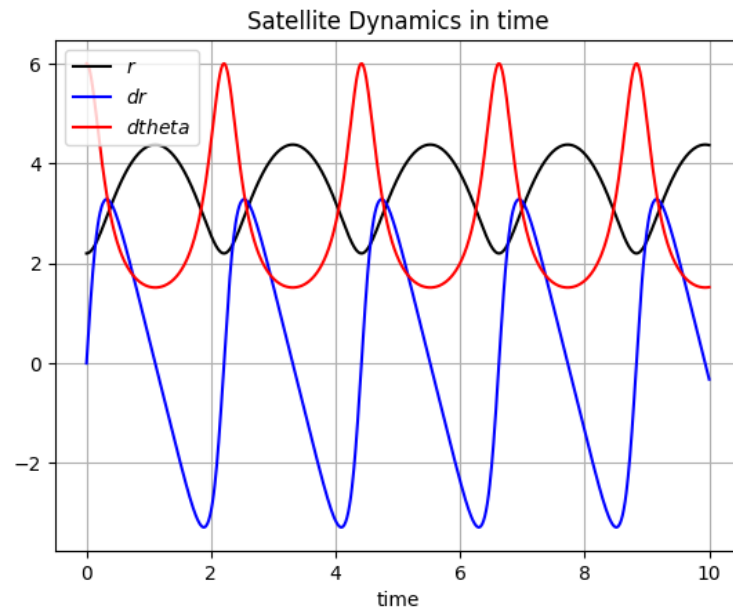
#plot

plt.figure(1)
plt.plot(t, x1, 'k-', label='$r$')
plt.plot(t, x2, 'b-', label='$dr$')
#plt.plot(t, x3*360/6.28, 'g-', label='$\theta$')
plt.plot(t, x4, 'r-', label='$d \theta$')
plt.title("Satellite Dynamics in time")
plt.xlabel("time")
plt.grid()
plt.legend(loc='best')

plt.figure(2)
# setting the axes projection as polar
plt.axes(projection = 'polar')
plt.polar(x3, x1, 'r-')

```

Out[12]: [



2.3

Consider the dynamics of the error to the nominal trajectory x_0 , that is $y = x - x_0$

Linearize the system. Notice that although x_0 is time-varying, the linearized error dynamics is autonomous. Why?

2.4

Simulate the linearized system. Compare the original nonlinear systems with the linearization plus the nominal system.

```
In [ ]: # To complete

import numpy as np
#import control

r0 = 10
omega = 1
A = np.array([\
    [ , , ],\
    [ , , ],\
    [ , , ],\
    [ , , ] ] )

B = np.array([\
    [0.0, 0.0],\
    [0.0, 1.0],\
    [0.0, 0.0],\
    [0.0, 0.0] ] )

print ( 'A\n', A )
print ( 'B\n', B )

eig_open_loop, eig_vect = np.linalg.eig( A )
print ( 'Eigenvalues of A \n', eig_open_loop )
```

```
In [ ]: # Solution

import numpy as np
#import control

r0 = 10
omega = 1
A = np.array([\
    [0.0, 1.0, 0.0, 0.0],\
    [3*omega**2, 0.0, 0.0, 2*r0*omega],\
    [0.0, 0.0, 0.0, 1],\
    [0.0, -2*omega/r0, 0.0, 0.0] ] )

B = np.array([\
    [0.0, 0.0],\
    [0.0, 1.0],\
    [0.0, 0.0],\
    [0.0, 0.0] ] )

print ( 'A\n', A )
print ( 'B\n', B )

eig_open_loop, eig_vect = np.linalg.eig( A )
print ( 'Eigenvalues of A \n', eig_open_loop)
```

```
A
[[ 0.   1.   0.   0. ]
 [ 3.   0.   0.  20. ]
 [ 0.   0.   0.   1. ]
 [ 0. -0.2  0.   0. ]]

B
[[0. 0.]
 [0. 1.]
 [0. 0.]
 [0. 0.]]

Eigenvalues of A
[0.+0.j 0.+1.j 0.-1.j 0.+0.j]
```

2.5

Where are the open-loop poles of the linearized system. Is it controllable?

Consider its subsystem $\dot{z} = \bar{A}z + \bar{B}v$ with $z = [r \ \dot{r}]$ and $v = T$. Check that the subsystem is controllable. Find a linear feedback matrix K such that $v = -Kz$ places the poles at -1 and -2.

```
In [ ]: pip install control
```

```
Collecting control
  Downloading control-0.9.4-py3-none-any.whl (455 kB)
    455.1/455.1 kB 4.0 MB/s eta
0:00:00
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-pa
ckages (from control) (1.25.2)
Requirement already satisfied: scipy>=1.3 in /usr/local/lib/python3.10/di
st-packages (from control) (1.11.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/di
st-packages (from control) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python
3.10/dist-packages (from matplotlib->control) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/
dist-packages (from matplotlib->control) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python
3.10/dist-packages (from matplotlib->control) (4.49.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python
3.10/dist-packages (from matplotlib->control) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.
10/dist-packages (from matplotlib->control) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.1
0/dist-packages (from matplotlib->control) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python
3.10/dist-packages (from matplotlib->control) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/pyt
hon3.10/dist-packages (from matplotlib->control) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist
-packages (from python-dateutil>=2.7->matplotlib->control) (1.16.0)
Installing collected packages: control
Successfully installed control-0.9.4
```

```

In [ ]: # To complete
import control

# Controllability
print ('---Controllability')
print ('rank of ctrb(A,b)', np.linalg.matrix_rank( control.ctrb( A, B )
print ('Eigenvalues of A ', np.linalg.eig( A )[0])

#Sun-system
r0 = 2
omega= 6
A1 = np.array([\
    [ , ],\
    [ , ] ] )

B1 = np.array([\
    [0.0],\
    [1.0] ] )

print ('A1\n', A1)
print ('B1\n', B1)

eig_open_loop, eig_vect = np.linalg.eig( A1 )
print ('Eigenvalues of A1 \n', eig_open_loop)

# Pole Placement
K = control.place( A1, B1, [-1, -2] )
print ('---Pole Placement\nK=\n', K)

# Verification of Eigen values of A-BK
print ('\n---Verification of Eigenvalues of A-BK\n')
Acl = A1-B1@K
#print(Acl)
eig_Acl, eig_vect = np.linalg.eig( Acl )
print ('Eigenvalues of A-BK:', eig_Acl)

```

```

In [ ]: # Solution
import control

# Controllability
print ('---Controllability')
print ('rank of ctrb(A,b)', np.linalg.matrix_rank( control.ctrb( A, B )
print ('Eigenvalues of A ', np.linalg.eig( A )[0])

#Sun-system
r0 = 2
omega= 6
A1 = np.array([\
    [0.0, 1.0],\
    [3*omega**2, 0.0] ] )

B1 = np.array([\
    [0.0],\
    [1.0] ] )

print ('A1\n', A1)
print ('B1\n', B1)

eig_open_loop, eig_vect = np.linalg.eig( A1 )
print ('Eigenvalues of A1 \n', eig_open_loop)

# Pole Placement
K = control.place( A1, B1, [-1, -2] )
print ('---Pole Placement\nK=\n', K)

# Verification of Eigen values of A-BK
print ('\n---Verification of Eigenvalues of A-BK\n')
Acl = A1-B1@K
#print(Acl)
eig_Acl, eig_vect = np.linalg.eig( Acl )
print ('Eigenvalues of A-BK:', eig_Acl)

---Controllability
rank of ctrb(A,b) 3
Eigenvalues of A  [0.+0.j 0.+1.j 0.-1.j 0.+0.j]
A1
[[ 0.  1.]
 [108.  0.]]
B1
[[0.]
 [1.]]
Eigenvalues of A1
[ 10.39230485 -10.39230485]
---Pole Placement
K=
[[110.  3.]]

---Verification of Eigenvalues of A-BK
Eigenvalues of A-BK: [-1. -2.]

```

2.6

Simulate the complete system with the designed controller. Start from initial points outside the nominal trajectory.

```
In [ ]: # To complete

import numpy as np
from scipy import integrate
import matplotlib.pyplot as plt
# show plots in notebook
# matplotlib inline

# parameters
r0=2
w=6
mu=(r0**3) * (w**2)

# vector field
def Sys_f(x, t=0):
    r=x[0]
    dr=x[1]
    th=x[2]
    dth=x[3]
    T = -K[0][0]*(r-r0)-K[0][1]*dr
    dx1=...
    dx2= ...
    dx3= ...
    dx4= ...
    return np.array([ dx1, dx2, dx3, dx4
                      ])

# generate 1000 linearly spaced points for t
t_end=10
t = np.linspace(0, t_end, 1000)

# initial values:
x0 = np.array([r0+0.2, 0.0, 0, w])

# integrate.odeint
x = integrate.odeint(Sys_f, x0, t, full_output=False)

x1,x2, x3, x4 = x.T

#plot

plt.figure(1)
plt.plot(t, x1, 'k-', label='$r$')
plt.plot(t, x2, 'b-', label='$dr$')
#plt.plot(t, x3*360/6.28, 'g-', label='$theta$')
plt.plot(t, x4, 'r-', label='$d theta$')
plt.title("Satellite Dynamics in time")
plt.xlabel("time")
plt.grid()
plt.legend(loc='best')

plt.figure(2)
# setting the axes projection as polar
plt.axes(projection = 'polar')
plt.polar(x1, x3, 'r-')
```



```

In [ ]: # Solution

import numpy as np
from scipy import integrate
import matplotlib.pyplot as plt
# show plots in notebook
# matplotlib inline

# parameters
r0=2
w=6
mu=(r0**3) * (w**2)

# vector field
def Sys_f(x, t=0):
    r=x[0]
    dr=x[1]
    th=x[2]
    dth=x[3]
    T = -K[0][0]*(r-r0)-K[0][1]*dr
    dx1=dr
    dx2= r * (dth*dth) - mu/(r*r)+T
    dx3=dth
    dx4= - 2 * dr * dth /r
    return np.array([ dx1, dx2, dx3, dx4
                      ])

# generate 1000 linearly spaced points for t
t_end=10
t = np.linspace(0, t_end, 1000)

# initial values:
x0 = np.array([r0+0.2, 0.0, 0, w])

# integrate.odeint
x = integrate.odeint(Sys_f, x0, t, full_output=False)

x1,x2, x3, x4 = x.T

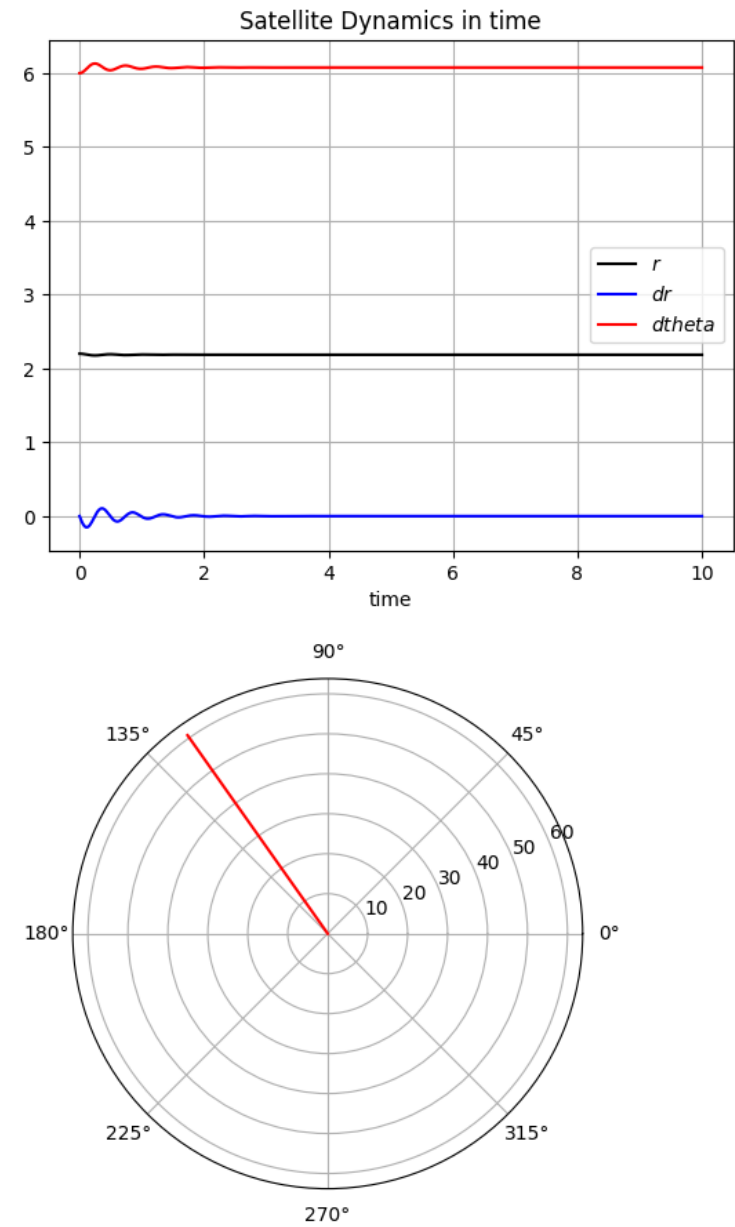
#plot

plt.figure(1)
plt.plot(t, x1, 'k-', label='$r$')
plt.plot(t, x2, 'b-', label='$dr$')
#plt.plot(t, x3*360/6.28, 'g-', label='$\theta$')
plt.plot(t, x4, 'r-', label='$d\theta$')
plt.title("Satellite Dynamics in time")
plt.xlabel("time")
plt.grid()
plt.legend(loc='best')

plt.figure(2)
# setting the axes projection as polar
plt.axes(projection = 'polar')
plt.polar(x1, x3, 'r-')

```

Out []: [<matplotlib.lines.Line2D at 0x7be546878520>]



2.7

Consider the function $V(x) = r^2 - r\dot{r} + \frac{1}{2}\dot{r}^2$. Use it to show that the linear subsystem is G.A.S.

What can you conclude about the stability of the complete linearized system using V ?

What can you conclude about the original nonlinear system?