Artificial bee colony optimized controller for unmanned rotorcraft pendulum

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Abstract
Purpose – The purpose of this paper is to propose a new algorithm for pendulum-like oscillation control of an unmanned rotorcraft (UR) in a reconnaissance mission and improve the stabilizing performance of the UR’s hover and stare.

Design/methodology/approach – The algorithm is based on linear-quadratic regulator (LQR), of which the determinable parameters are optimized by the artificial bee colony (ABC) algorithm, a newly developed algorithm inspired by swarm intelligence and motivated by the intelligent behaviour of honey bees.

Findings – The proposed algorithm is tested in a UR simulation environment and achieves stabilization of the pendulum oscillation in less than 4s.

Research limitations/implications – The presented algorithm and design strategy can be extended for other types of complex control missions where relative parameters must be optimized to get a better control performance.

Practical implications – The ABC optimized control system developed can be easily applied to practice and can safely stabilize the UR during hover and stare, which will considerably improve the stability of the UR and lead to better reconnaissance performance.

Originality/value – This research presents a new algorithm to control the pendulum-like oscillation of URs, whose performance of hover and stare is a key issue when carrying out new challenging reconnaissance missions in urban warfare. Simulation results show that the presented algorithm performs better than traditional methods and the design process is simpler and easier.

Keywords Aircraft, Programming and algorithm theory, Controllers, Oscillations, Unmanned rotorcraft, Pendulum oscillation, Artificial bee colony, Linear quadratic regulator

Paper type Research paper

Introduction
Micro aerial vehicles (MAVs), essentially small scale flying robots, became an area of interest in the aerospace community with the initiation of the micro UAV (MUAV) program by Defense Advanced Research Projects Agency (DARPA) (Month et al., 2004). The technological feasibility of MAVs as one possible solution to new challenging reconnaissance mission scenarios in urban warfare (local, close-up range, hidden reconnaissance, operation between obstacles and maybe even inside buildings) is depending on a bunch of questions, which are only partly answered so far.

One of the challenging problems for MAVs is to design a robust flight control system for such a miniaturized “bird”, which is generally one order of magnitude smaller than any today’s operational unmanned aerial vehicle (UAV) (Fu et al., 2012). Richard and Stefan (2004) put forward several unique, very challenging operational requirements associated with the guidance, navigation and control of an MAV, which in combination and at the scale of an MAV sound rather futuristic. A simple, nonlinear closed-loop control law was designed for the dynamics along the vertical and pitch axis of a flapping-wing MAV, allowing an efficient stabilization of the naturally unstable model (Thomas et al., 2010). The aerodynamic modelling of a ducted fan vertical take off and landing (VTOL) UAV and the problem of attitude stabilization was studied when the vehicle is remotely controlled by a pilot in presence of crosswind (Pflimlin et al., 2010).

The recent boom of bio-inspired algorithms, which are derived from biological inspired self-organized systems as found in biological evolution, foraging insects (ants, bees, etc.), and flocking birds and attack activities (bees, wasps, etc.), has attracted increasingly more researchers to the field of applying such intelligent approaches to optimization problems in modelling and control of UAVs (Duan and Li, 2012). A parallel hybrid algorithm for solving global optimization problems is proposed (Velazquez et al., 2010), which is based on the coupling a stochastic global (simultaneous perturbation stochastic approximation, simulated annealing, and genetic algorithms (GAs)) and a local method (Newton-Krylov Interior-Point) via a surrogate model, and solved the wing modelling problem of an MAV. The hybrid algorithm combined the advantages of more than one computing methods and greatly improved the global search ability. Zhou et al. (2012) combined ant colony optimization (ACO) with Voronoi diagram and developed an efficient route planning method for UAVs. A new variant of particle swarm optimization (PSO), named phase angle-encoded and quantum-behaved particle swarm optimization (u-PSO), was developed (Fu et al., 2012). Due to
is proposed. The ABC algorithm is used for parameter optimization of weighting matrix $Q$ in LQR, which makes controller design much easier for engineers. To the best knowledge of the authors, there is no existing literature that deals UP pendulum-like oscillation by combination of ABC and LQR. Series of simulation experiments and comparison are conducted, and the results verify the feasibility and effectiveness of our proposed approach.

The rest of the paper is organized as follows. The second section introduces the pendulum oscillation of the UR and deduces the mathematical model. The ABC algorithm, which is used as an optimizer for the controller parameters, is described in the third section. The main part of the paper follows in the fourth section, which gives a detailed description of the proposed approach to pendulum control that combines LQR and the hybrid optimization algorithm motivated by swarm intelligence. The simulation and comparison results using a UR are presented in the fifth section. The sixth section concludes the paper and future work is shown in the last section.

**Mathematical model of pendulum oscillation**

**Nonlinear model**

The pendulum of a UR can be abstracted as a system consisting of the suspension point $O_h$, the pendulum rod $O_hO$, and the pendulum mass $O$, as shown in Figure 3 (Wang, 2009). OXYZ is the ground-fixed coordinate system; $O_{x1y1z1}$ is a mobile ground coordinate system, with point $O_h$ as the origin and parallel to OXYZ, while $O_{x1y1z2}$ is a pendulum-body coordinate frame, which originates from $O_h$ and axis $z_2$ points downward along the pendulum rod $O_hO$. Decompose the two-dimension pendulum oscillation to oscillation in the direction of axis $X$ and $Y$, and the transition matrix $T$ from $O_{x1y1z2}$ to $O_{x1y1z1}$ is obtained as follows:

$$ T = \begin{bmatrix} \cos \theta_2 & \sin \theta_2 & \cos \theta_3 & \sin \theta_3 & 0 \\ 0 & \cos \theta_3 & -\sin \theta_3 & 0 & 0 \\ -\sin \theta_2 & \sin \theta_2 & \cos \theta_3 & 0 & 0 \end{bmatrix} $$ \hspace{1cm} (1)

Suppose the position vector of the suspension point $O_h$ in coordinate frame OXYZ and the pendulum mass $O_i$ in coordinate frame $O_{x1y1z2}$ are presented, respectively, as follows:

$$ r_h = [x, y, z]^T, \quad r'_i = [0, 0, l]^T $$

**Figure 1** Pendulum oscillations in axis $X$; pendulum oscillation in actual flight
Figure 2 UR with a single rotor and ducted fan

Figure 3 Coordinates of the pendulum model

Then the coordinate of point $O_t$ in $O_bx_0y_0z_0$ is calculated:

$$r_{bt} = r_b + T \cdot r'_t$$

(2)

Finally, the coordinate of $O_t$ in coordinate frame $OXYZ$ is obtained as the following procedures:

$$r_t = r_{bt} + T \cdot r'_t$$

(3)

Lagrange function of the pendulum system:

$$L = T_0 - V = T_m + T_M + T'_{M'} - V$$

$$= \frac{1}{2} m_r^2 \dot{r}_b + \frac{1}{2} m_r V_0^2 T + \frac{1}{2} \frac{J_{z2} \omega_{z2}^2}{2} + \frac{1}{2} \frac{J_{y2} \omega_{y2}^2}{2}$$

$$- (-m_g g \cos \theta_x \cos \theta_y + (m + m_t)(z - z_0) g)$$

$$= \frac{1}{2} (m + m_t)(\dot{x}^2 + \dot{y}^2 + \dot{z}^2)$$

(4)

where $T_m$, $T_M$, $T'_{M'}$ denotes, respectively, kinetic energy of the suspension center $O_b$, translation kinetic energy of the pendulum mass $O_t$, rotational kinetic energy of the pendulum rod around the centroid of $O_b$, and $V$ is potential energy of the system, setting the initial state of the pendulum oscillation as zero-potential energy surface.

Thus, equation (5) can be deduced from Lagrange equation:

$$\begin{align*}
\frac{d}{dt} \frac{\partial L}{\partial \dot{\theta}_x} - \frac{\partial L}{\partial \theta_x} &= 0 \\
\frac{d}{dt} \frac{\partial L}{\partial \dot{\theta}_y} - \frac{\partial L}{\partial \theta_y} &= 0
\end{align*}$$

(5)

Considering all the above equations (1)-(5), the nonlinear mathematical model of the pendulum oscillation is finally presented in equation (6):

$$\begin{align*}
\ddot{\theta}_x &= (3 \ddot{x} \sin \theta_x \sin \theta_y + 3 \cos \theta_x + 3 \sin \theta_x \cos \theta_y) \\
& + 2l \ddot{\theta}_x \dot{\theta}_y \cos \theta_y - 3l \ddot{\theta}_y \sin \theta_x \cos \theta_y \\
& - 3g \sin \theta_x \cos \theta_y / (\cos^2 \theta_x + 3) l \\
\ddot{\theta}_y &= (3 l \ddot{y} \sin \theta_x + 3 \ddot{z} \cos \theta_x \sin \theta_y + 6l \ddot{\theta}_x \sin \theta_x \cos \theta_y \\
& - 3g \cos \theta_x \sin \theta_y / (\cos^2 \theta_x + 3) l
\end{align*}$$

(6)

Table I shows the main parameters of the equivalent pendulum system structure.

**Model linearization**

The linear model of the pendulum phenomenon of the UR is obtained as the following procedures:

1. Change pendulum angle ($\theta_x$, $\theta_y$) around axis $x$, $y$ to pitch and roll angle ($\phi_x$, $\phi_y$) according to $\phi_x = \theta_x$, $\phi_y = -\theta_y$, and then equation (6) is described (Jiang, 2008):

$$\begin{align*}
\ddot{\phi}_x &= (3 \ddot{x} \sin \phi_x \sin \phi_y + 3 \ddot{y} \cos \phi_x + 3 \ddot{z} \sin \phi_x \cos \phi_y) \\
& + 2l \ddot{\phi}_x \dot{\phi}_y \cos \phi_y - 3l \ddot{\phi}_y \sin \phi_x \cos \phi_y \\
& - 3g \sin \phi_x \cos \phi_y / (\cos^2 \phi_x + 3) l \\
\ddot{\phi}_y &= (3 \ddot{y} \sin \phi_x \cos \phi_y + 3 \ddot{z} \cos \phi_x \sin \phi_y + 6l \ddot{\phi}_x \sin \phi_x \cos \phi_y \\
& - 3g \cos \phi_x \sin \phi_y / (\cos^2 \phi_x + 3) l
\end{align*}$$

(7)

<p>| Table I Main parameters of the pendulum system structure |</p>
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Physical meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m$</td>
<td>10 kg</td>
<td>Mass of suspension centre</td>
</tr>
<tr>
<td>$m_r$</td>
<td>20 kg</td>
<td>Pendulum mass</td>
</tr>
<tr>
<td>$l$</td>
<td>0.86 m</td>
<td>Pendulum length</td>
</tr>
<tr>
<td>$g$</td>
<td>9.8 m/s²</td>
<td>Gravitational acceleration</td>
</tr>
<tr>
<td>$\theta_x$, $\theta_y$</td>
<td></td>
<td>Pendulum angle around axis $x$, $y$</td>
</tr>
<tr>
<td>$\phi_x$, $\phi_y$</td>
<td></td>
<td>Pitch and roll angle</td>
</tr>
<tr>
<td>$a_x$, $a_y$</td>
<td></td>
<td>Suspension centre acceleration</td>
</tr>
<tr>
<td>$u_x$, $u_y$</td>
<td></td>
<td>Control input on $O_b$</td>
</tr>
</tbody>
</table>
Choose the state variables $X_s = [x, \phi_x, \dot{x}, \phi_y, \dot{y}, z, \dot{z}, \dot{x}, \dot{y}, \dot{z}]^T$, input of the system $u = [\dot{x}, \dot{y}]^T$. Expand equation (7) into Taylor series in the vicinity of the equilibrium point and the linear model of the pendulum oscillation is finally obtained as below:

$$
\begin{bmatrix}
X_x \\
X_y
\end{bmatrix} = 
\begin{bmatrix}
A_x & 0 \\
0 & A_y
\end{bmatrix}
\begin{bmatrix}
X_x \\
X_y
\end{bmatrix} + 
\begin{bmatrix}
B_x & 0 \\
0 & B_y
\end{bmatrix}
\begin{bmatrix}
u_x \\
u_y
\end{bmatrix}
$$

(8)

where the state vector $X_s = [x, \phi_x, \dot{x}, \phi_y, \dot{y}]^T$, and:

$$
A_x = \begin{bmatrix}
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 \\
0 & -\frac{3\pi}{4} & 0 & 0
\end{bmatrix},
A_y = \begin{bmatrix}
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix},
$$

$$
B_x = \begin{bmatrix}
0 \\
0 \\
1 \\
-\frac{3\pi}{4}
\end{bmatrix},
B_y = \begin{bmatrix}
0 \\
1 \\
-\frac{\pi}{4}
\end{bmatrix}.
$$

Characteristic analysis
As can be seen, oscillation in the direction of $X$ and $Y$ is decoupled with each other. Thus, the pendulum system is reduced to two four-order subsystems, which are independent of one another. Owing to similarity between matrix $A_x$ and $A_y$, either of the two subsystems is considered to analyze characteristics of pendulum oscillation.

Considering pendulum motion only in the direction of axis $X$ and taking actual parameters into account, the state space equation of the $X$-subsystem is presented as follows:

$$
\begin{align*}
\dot{X} &= AX + BU \\
Y &= CX
\end{align*}
$$

(9)

where $X = [x_1, x_2, x_3, x_4]^T = [x, \phi_x, \dot{x}, \phi_x]^T$:

$$
A = \begin{bmatrix}
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & -0.6500 & 0.6500 \\
0 & -8.547 & 0.5669 & -0.3924
\end{bmatrix},
$$

$$
B = \begin{bmatrix}
0 \\
0 \\
1 \\
-0.872
\end{bmatrix},
C = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}.
$$

The zero-input response of the pendulum oscillation system (9) in Figure 4 shows that the initial state triggers pendulum oscillation and the oscillation amplitude attenuates with time. Besides, the position and velocity of the suspension center also fluctuates with slight amplitude. The oscillation characteristic takes more than 20s to die away, which inevitably leads to performance degradation such as blurred images and calls for a control system to eliminate disturbances.

ABC algorithm
ABC algorithm was first proposed by simulating the self-organization simulation model of honey bees (Seeley, 1995). In this model, although each bee only performs one single task, yet through a variety of information communication ways between bees, the entire colony can complete a number of complex works such as hives building, pollen harvest and so on. Then a bee colony optimization (BCO) algorithm was further introduced (Teodorovic and Orco, 2005). And in 2007, Karaboga and Basturk (2007) put forward an improved ABC algorithm.

Compared with conventional bio-inspired algorithms used for optimization problems, such as GA, PSO and so on, the ABC algorithm differs from them in that ABC simultaneously carries out local search and global search in the optimization space and can efficiently avoid trapping into local optimum, thus resulting in an excellent balance between exploitation and exploration, which makes ABC a more appropriate choice for parameter optimization in control system design.

Basic principles
Karlvon Frisch, a famous Nobel prize winner, once found that in nature, although each bee only performs one single task, yet through a variety of information communication ways between bees such as waggle dance and special odor, the entire colony can always easily find food resources that produce relative high amount nectar, hence realize its self-organizing behavior. In nature, the bees crawl along a straight line, and then turn left, moving as Figure 5 and swinging their belly (Fathian et al., 2007; Duan et al., 2010a, b). Such a dance is called waggle dance, and the angle between the gravity direction and the center axis of the dance is exactly equal to the angle between the sun and food source (Figure 5).

In addition, waggle dance of the bees can also deliver more detailed information about the food sources such as distance and direction. When bees are dancing, head up means they should fly towards the sun in order to find the food source location, while head down indicates flying backwards the sun. Besides, dancing speed of the bees is closely related with the distance between current position and food source location. The longer the distance is, the longer the time for bees swinging. Then each bee in the hive selects a food source to search for nectar, or researches new food sources around the bee hive, according to the information delivered by the other bee’s waggle dance (Singh, 2009). In this way, through this kind of information exchanging and learning, the whole colony would always find relatively prominent nectar source.

In order to introduce the model of forage selection that leads to the emergence of collective intelligence of honey bee swarms, three essential components are defined: food sources, unemployed foragers and employed foragers:

1. Food sources (A and B in Figure 6): for the sake of simplicity, the “profitability” of a food source can be represented with a single quantity (Singh, 2009). In our target recognition problem, the position of a food source represents a possible parameters solution to the optimization problem and the nectar amount of a food source corresponds to the similarity value of the associated solution.

2. Unemployed foragers: if it is assumed that a bee has no knowledge about the food sources in the search field, the bee initializes its search as an unemployed forager. Unemployed foragers are continually at look out for a
food source to exploit. There are two types of unemployed foragers: scouts and onlookers.

3 Employed foragers: they are associated with a particular food source which they are currently exploiting. They carry with them information about this particular source, the profitability of the source and share this information with a certain probability. After the employed foraging bee loads a portion of nectar from the food source, it returns to the hive and unloads the nectar to the food area in the hive.

At the initial moment, all the bees without any prior knowledge play the role of detecting bees. After a random search for bee sources, the detecting bees can convert into any kind of bees above in accordance with the profit of the searched food sources.

Mathematical description

Define $N_s$ as the total number of bees, $N_e$ as the colony size of the employed bees and $N_u$ as the size of unemployed bees, which satisfy the equation $N_s = N_e + N_u$. We usually set $N_e$ equal to $N_u$. $D$ is the dimension of individual solution vector, $S = R^D$ represents individual search space, and $S^{N_e}$ denotes the colony space of employed bees. An employed bee colony can be expressed by $N_e$ dimension vector $\bar{X} = (X_1, \ldots, X_{N_e})$, where $X_i \in S$ and $i \leq N_e$. $\bar{X}(0)$ means the initial employed bee colony, while $\bar{X}(n)$ represents employed bee colony in the $n$th iteration. Denote $f : S \rightarrow R^+$ as the fitness function, and the standard ABC algorithm can be expressed as follows:

- **Step 1.** Randomly initialize a set of feasible solutions $(X_1, \ldots, X_{N_s})$, and the specific solution $X_i$ can be generated by:

$$X'_i = X'_\text{min} + \text{rand}(0, 1)(X'_\text{max} - X'_\text{min})$$

where $i \in \{1, 2, \ldots, D\}$ is the $i$th dimension of the solution vector. $X'_\text{max}$ means the maximum value of the $j$th element of a solution. By the same token, $X'_\text{min}$ means the minimum value of the $j$th element of a solution. $X'_\text{max}$ and $X'_\text{min}$ are problem dependent and are chosen to constrain the candidate solution in a specified search space. Calculate the fitness value of each solution vector, respectively, and set the top $N_e$ best solutions as the initial population of the employed bees $\bar{X}(0)$.
Figure 6 The behavior of honey bee foraging for nectar

- **Step 2.** For an employed bee in the $n$th iteration $X_i(n)$, search new solutions in the neighborhood of the current position vector according to the following equation:

$$V'_i = X'_i + \varphi'_i(X_i - X_k)$$

where $V \in S, j \in \{1, 2, \ldots, D\}, k \in \{1, 2, \ldots, N_s\}, k \neq i$, $k$ and $j$ are randomly generated, $\varphi'_i$ is a random number between $-1$ and 1.

Generally, this searching process is actually a random mapping from individual space to individual space, and this process can be denoted with $T_m: S \rightarrow S$, and its probability distribution is clearly only related to current position vector $X_i(n)$, and has no relation with past location vectors as well as the iteration number $n$:

- **Step 3.** Apply the greedy selection operator $T_i: S^2 \rightarrow S$ to choose the better solution between searched new vector $V_i$ and the original vector $X_i$ into the next generation. Its probability distribution can be described as follows:

$$P[T_i(X_i, V_i) = V_i] = \begin{cases} 1, & f(V_i) \leq f(X_i) \\ 0, & f(V_i) < f(X_i) \end{cases}$$

The greedy selection operator ensures that the population is able to retain the elite individual, and accordingly the evolution will not retreat. Obviously, the distribution of $T_i$ is has no relation with the iteration $n$:

- **Step 4.** Each unemployed bee selects an employed bee from the colony according to their fitness values. The probability distribution of the selection operator $T_{ni}: S^{N_s} \rightarrow S$ can be described as follows:

$$P[T_{ni} \tilde{X} = X_i] = \frac{f(X_i)}{\sum_{m=1}^{N_s} f(X_m)}$$

- **Step 5.** The unemployed bee searches in the neighborhood of the selected employed bee’s position to find new solutions. The updated best fitness value can be denoted with $f_{best}$, and the best solution parameters can be expressed by $(x_{11}, x_{22}, \ldots, x_{D2})$

- **Step 6.** If the searching times surrounding an employed bee Bas exceeds a certain threshold Limit, but still could not find better solutions, then the location vector can be re-initialized randomly according to the following equation:

$$X_i(n + 1) = \begin{cases} X_{min} + rand(0, 1)(X_{max} - X_{min}), & Bas \geq Limit \\ X_i(n), & Bas < Limit \end{cases}$$

(14)

- **Step 7.** If the iteration value is larger than the maximum number of the iteration (that is, $T > T_{max}$), output the optimal fitness value $f_{best}$ and correlative parameters $(x_{11}, x_{22}, \ldots, x_{D2})$. If not, go to Step 2.

Step 6 is a most prominent aspect making ABC algorithm different from other algorithms, which is designed to enhance the diversity of the population to prevent the population from trapping into the local optimum (Duan et al., 2010a, b). Obviously, this step can improve the probability of finding the best solution efficiently, and make the ABC algorithm perform much better. The flow chart of the basic ABC algorithm is given in Figure 7.

### Proposed controller

LQR is about how to select an appropriate control vector $u(t)$ so that the given quadratic performance index, equation (15), obtains the minimum value. It is proved that the performance index (15) shall reach its minimum by means of linear control law in equation (16):

$$J = \int_{0}^{\infty} (x^T Q x + u^T R u) dt$$

(15)

$$u(t) = -K X(t) = R^{-1} B^T P X(t)$$

(16)

and the optimal matrix $P$ can be calculated from Algebraic Riccati equation:

$$A^T P + P A - P B R^{-1} B^T P + Q = 0$$

(17)

Taking all factors into account, including performance of the control system and restrictions on the total energy consumed, matrices $Q$ and $R$ are chosen to have the form of:

$$Q = \text{diag}(q_{11}, q_{22}, 0, 0), R = 1$$

in which parameters $q_{11}$ and $q_{22}$ are to be optimized to acquire desired control performance. Let input $u$ be acceleration of the suspension center, and the corresponding pendulum-holding back control law is given in the following form:

$$u = -K X = R^{-1} B^T P X(t)$$

$$= -(k_1 x_1 + k_2 x_2 + k_3 x_3 + k_4 x_4)$$

(18)

where the control input $u$ is calculated from a full state feedback, of which the feedback gains $[k_1, k_2, k_3, k_4]$ are calculated from the optimized LQR.
The ABC optimized control system based on LQR is demonstrated as in Figure 8. The proposed controller has a full state feedback structure, whose control input $u_c$ is a linear combination of all the states $x_1, x_2, x_3,$ and $x_4$. The feedback gains $k_1, k_2, k_3,$ and $k_4$ are derived from the LQR approach, whose weighting matrix $Q$ is optimized by ABC offline. The actual control signal acting upon the pendulum is $u_a$, which is the sum of $x_g$ and $u_c$. Here $x_g$ can be seen as a disturbance factor. The full state feedback structure and the ABC optimized weighting matrix $Q$ in LQR facilitate the control system design and guarantee stability of the closed loop system. Finally the actual control signal $u_a$ is obtained by equation (18) and $x_g$ to regulate the plant to the desired equilibrium.

The implementation procedure of our proposed ABC optimized LQR controller can be described as follows:

- **Step 1.** According to actual wind tunnel test data and main parameters of the system structure in Table I, establish the nonlinear mathematical model of pendulum oscillation (equation (6)).
- **Step 2.** Expand the nonlinear mathematical model into Taylor series in the vicinity of the equilibrium point, and obtain the linear model of the pendulum oscillation, see equation (8).
- **Step 3.** Set the performance index $J$, the weighting matrices $Q$ and $R$.
- **Step 4.** Optimize the designed control law using the ABC algorithm, where parameters $q_{11}$ and $q_{22}$ are to be optimized using the fitness function of:
  \[ f := 1/50^6 \int_0^\infty (X^T Q X + u^T R u)dt \]
Step 5. Solve the Algebraic Riccati equation in equation (17) and get the matrix $P$.
Step 6. Calculate the feedback gain vector:

$$K = -R^{-1}B^TP$$

Step 7. Obtain the optimized control law:

$$u = -KX = R^{-1}B^TPX(t)$$

The flow chart of the proposed controller is shown in Figure 9.

**Simulation results**

Assuming that the UR is executing a surveillance mission using the hover and stare mode in the actual flight environment. Due to external disturbances, take cross winds for example, the system gets an initial state $x = [0, 0.05, 0, 0]$, which would otherwise give rise to pendulum oscillation (Figure 4) without an appropriate controller.

Tables II and III show the simulation parameters of ABC and PSO, which is used for comparison to verify the feasibility of ABC. Figure 10 shows the evolution curves of...
ABC and PSO, signified, respectively, by the thin dot line and the thick line. The figure demonstrates that the fitness function $f(x)$ increases as the generation iterates with time, gradually converging to an optimal result. It can be seen from the figure that ABC achieves a better result with a higher fitness value after 20 iterations of optimization, though it possesses a worse initial population due to some random reason. However, the PSO algorithm fails to find a satisfying solution of the optimization problem compared to ABC, although it has a better initialization process.

Using the ABC based LQR controller shown as in Figure 8 and experimental settings given above, control parameters which include the optimal weight matrix $Q$ and the resulting feedback vector $K$ are obtained as in Table IV.

The zero-input responses of the pendulum-like oscillation with an initial pendulum angle of 0.05 rad, which is brought about by cross winds in the actual flight environment, are shown in Figure 11. Compared with responses without control in Figure 4, the dynamic behaviors of $x$ and $\phi$, state clearly that the closed loop eliminates the pendulum-like oscillation and the state converges to the equilibrium point in an average time of 6 s which shortens the stabilizing time and improves the performance of UR’s hover and stare.

Furthermore, we consider a constant interference force acting upon the pendulum system besides the initial state. Here we assume there is a strong crosswind which acts upon the vehicle body and gives rise to a constant acceleration to the UR. The resulting responses are shown in Figure 12, where the constant acceleration is taken as 0.2 m/s$^2$ while the control framework and relative parameters remain the same as mentioned in Figure 8 and Table IV.

As shown in Figure 12, the ABC based LQR controller holds back the interference of the constant disturbance as well as the initial state in 6 s. The UR is stabilized to a state of $x = [0.024, 0, 0, 0]$, which means that the LQR control design technique based on ABC has a very nice robustness property and has the ability to restrain external disturbances. In this case, the UR’s performance of surveillance would be improved because more accurate and clearer images are taken due to the stability improvement of the hover and stare state.

**Conclusions**

The performance of hover and stare is the key issue to MAVs when carrying out new challenging reconnaissance missions in urban warfare (local, close-up range, hidden reconnaissance, operation between obstacles and maybe even inside buildings). However, pendulum-like oscillation caused by uncertainty will badly impair the performance of hover and stare, resulting in blurred images or even overturn. In this paper, a novel ABC optimized approach for pendulum control in a particular kind of UR with a ducted fan is described. This method takes advantage of the optimality and accuracy of LQR, and the ABC algorithm is adopted to optimize the weighting parameters. Series of experiments are conducted. Comparison with the PSO algorithm is carried out and shows that the ABC algorithm performs better than PSO in LQR optimization for the UR pendulum control. A constant disturbance is also incorporated into the model to investigate robustness of the proposed controller. Simulation results verify the feasibility, effectiveness and robustness of our proposed approach, which provides a more effective way for control law design.

**Further work**

Our future work will focus on how to apply the algorithm and the control law in the actual flight of a MAV with a ducted fan and try to improve its performance.
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Figure 11 Zero-input response with the proposed controller

Figure 12 Responses of the pendulum system with a constant disturbance

References


Further reading


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