# A Micromechanical Flying Insect

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- Overview of Project
- Aerodynamics
- Wings and Structure
- Actuators and Power Supply
- Sensors and Control

# Dragon Fly Data, *S. sanguineum*

- mass 0.121 gm, 49% muscle, peak muscle power $156 W kg^{-1}$
- resting 0.6 mW, hovering: 2 mW, high speed $2 m s^{-1}$: 10 mW
- efficiency $\approx$ 13%
- elastic storage 2.5 $J kg^{-1}$ or $100 W kg^{-1}$ at 40 Hz
- wing length 28 mm, stroke amplitude $150^\circ$

J.M. Wakeling and C.P. Ellington, "Dragon Fly Flight: III. Lift and Power Requirements" *Jnl. of Experimental Biology*, vol 200, pp. 583-600, 1997.

# Fruit Fly Data, *Drosophila*

- mass 1.05 mgm, 30% muscle, peak muscle power $77 W kg^{-1}$
- hovering: 19 $\mu W$, cruising: $0.5 ms^{-1}$: 24 $\mu W$,
- efficiency $6 < \eta < 10\%$
- wing velocity 1.4 - 2.2 $ms^{-1}$, flight force $16 \mu N$ peak
- wing stroke $120 - 170°$, beat 190-230 Hz, length 2.5 mm
- muscle stress $30 - 40 \times 10^3 N m^{-2}$, 1% strain

M.H. Dickinson and J.R.B. Lighton, “Muscle Efficiency and Elastic Storage in the Flight Motor of Drosophila”, *Science,* vol. 268, pp. 87-90, 7 April 1995.

# Speed and Range

Hoverfly

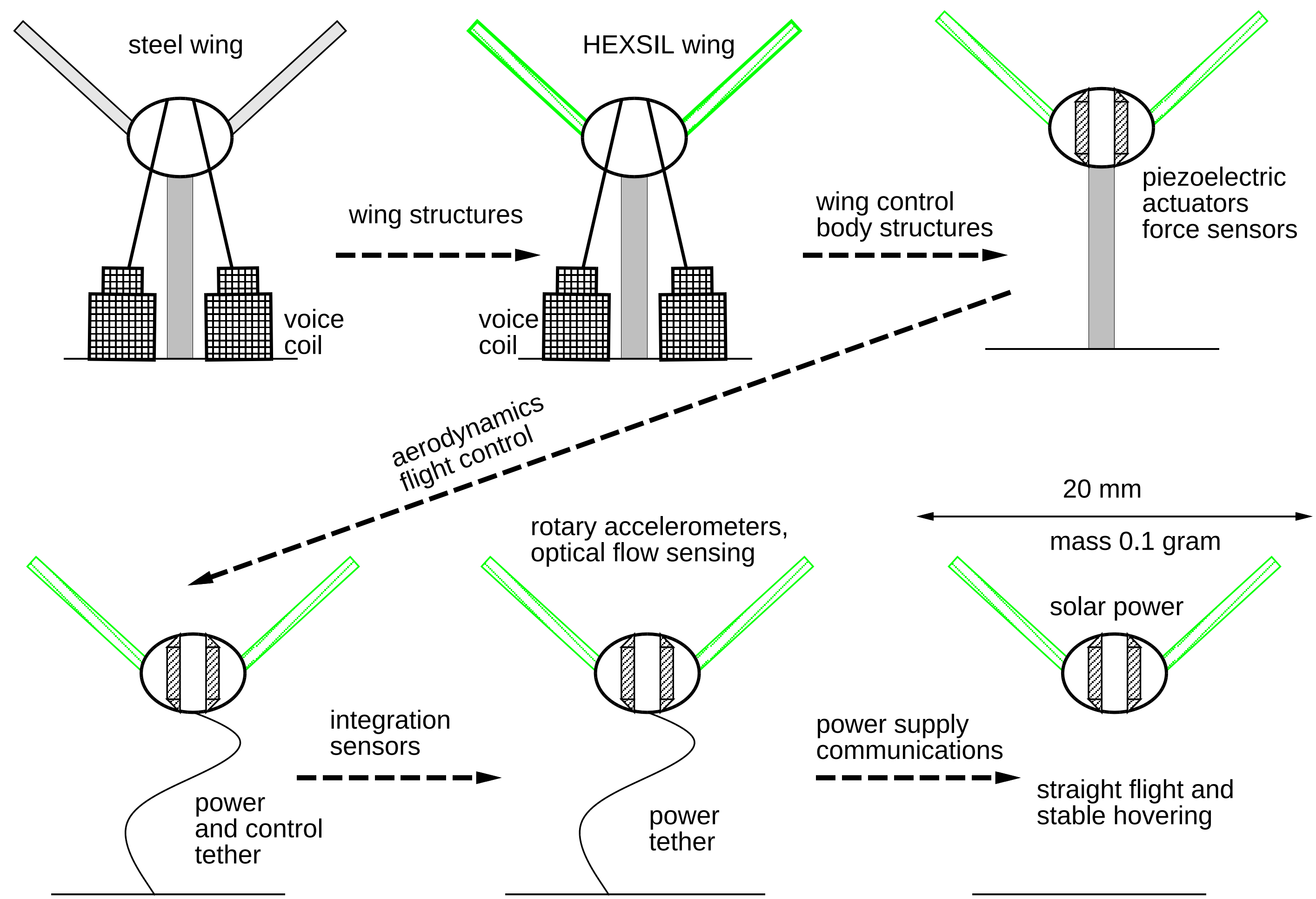
- burst speed 40 km $hr^{-1}$ ($11ms^{-1}$)

monarch butterfly

- cruise speed 18 km $hr^{-1}$ ($5ms^{-1}$)
- mass = 0.6 gram, fuel = 25% by weight fat
- range 800 km open loop, 4000 km using terrain and thermal features

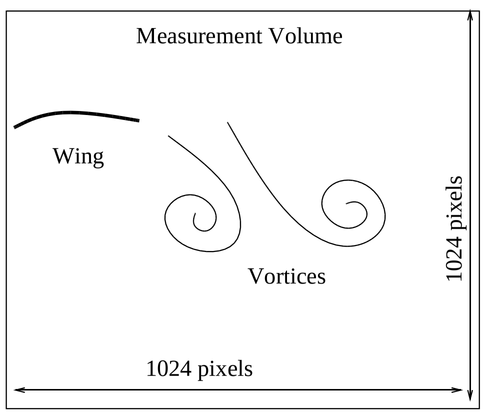
J. Brackenbury, *Insects in Flight*, London: Blandford.

# MFI Research Plan Overview



# Wing-Induced Flow Measurements

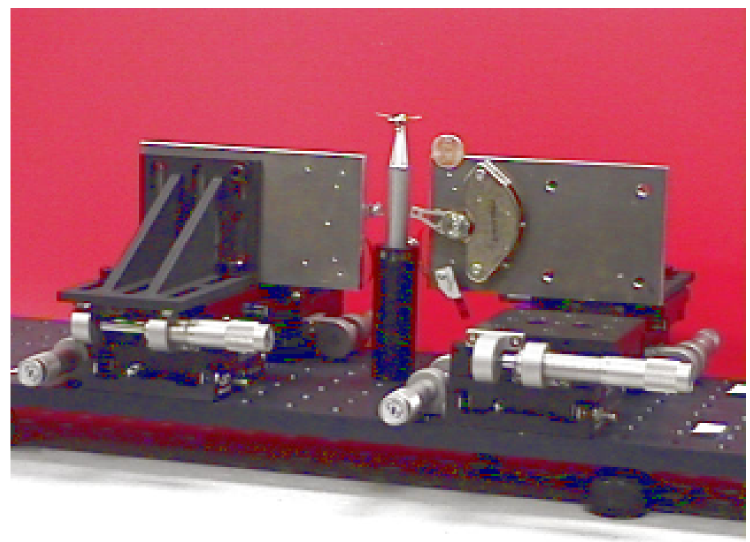
Compare fly and MFI vortices using Digital Particle Image Velocimetry (DPIV).



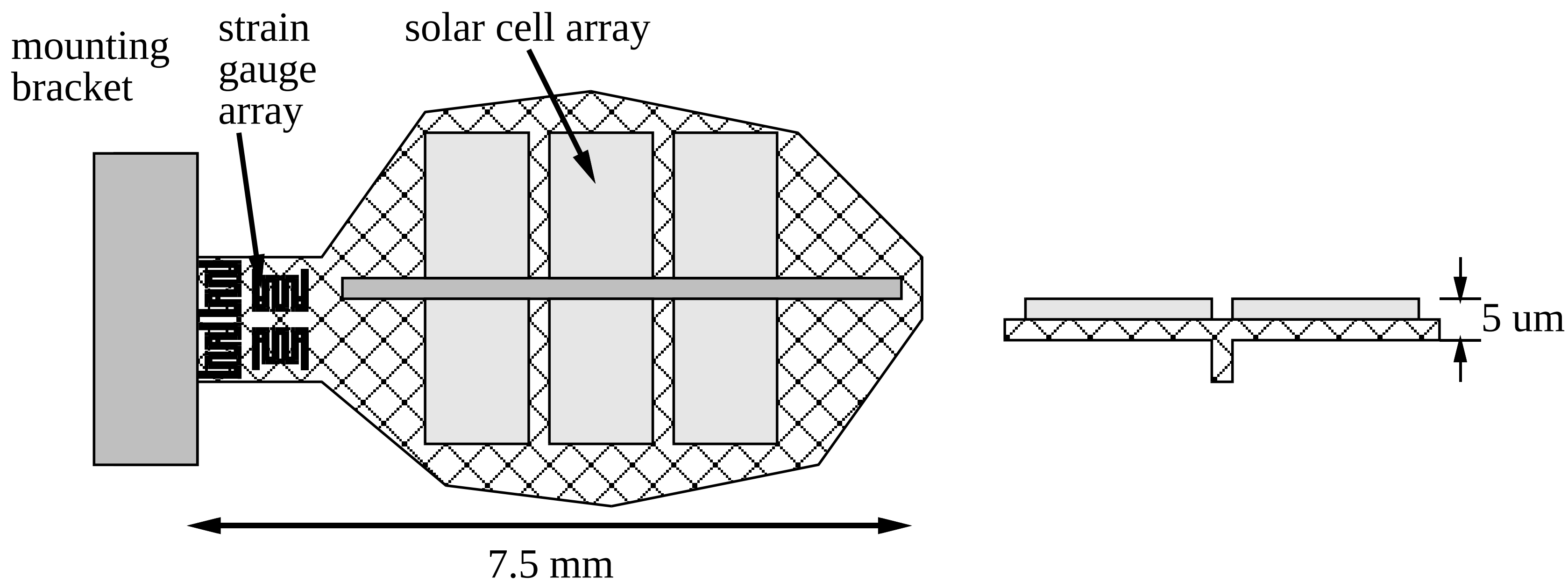

- time-resolved 2D velocity maps
- $1024 \times 1024$ CCD array camera
- 1 ms between sequential images
- max. velocity $10^5$ pixels/sec using new UCB algorithm
- particle seeding size $\approx 2\mu m$

(phase reconstruction required due to 15 Hz acquisition rate)

# Insect Mockup and Wing Tester

# Single face-sheet Hexsil wing



# Power Sources

**battery:**

$10^6 J/kg \Rightarrow \approx 1000$ seconds range with 10% efficiency

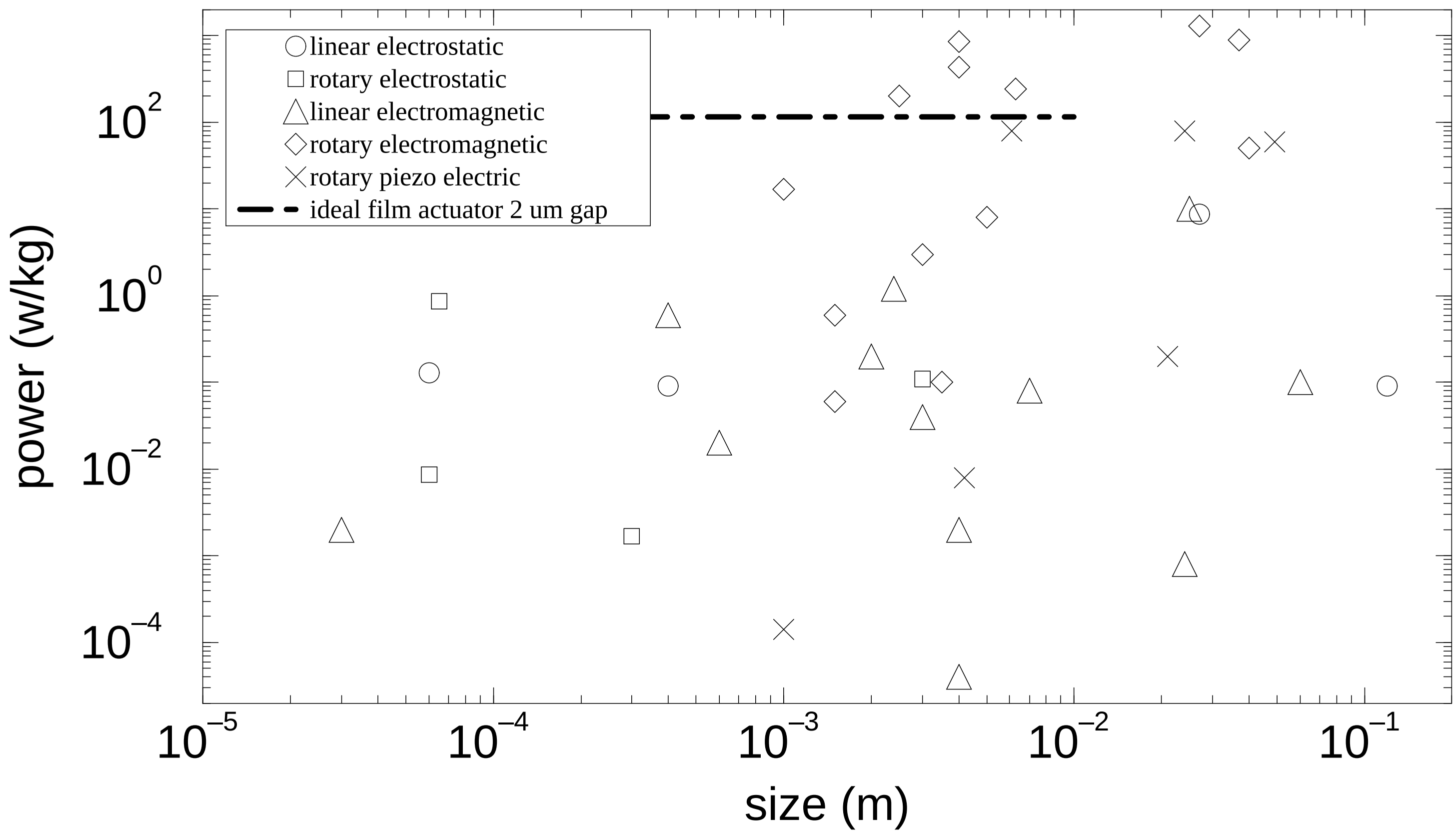
**solar cell:**

10% efficiency gives $10 mW cm^{-2}$

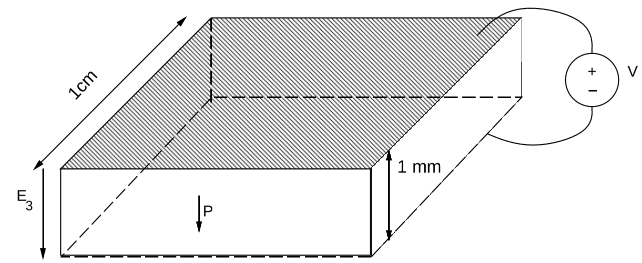
power requirement for 0.1 gm MFI with 1 $cm^2$ wing area: 4 mW

thin film solar cell: 2 $\mu m$ thick

# Comparison of actual micro-actuators



# Piezoelectric Power Limits




Power per volume: $\frac{P_o}{TWL} = \frac{\frac{1}{2} d_{31}^2 E^2 Q \omega_o}{s^E}$ $(2000 W cm^{-3})$

dynamic stress limit: $P_{max} = \frac{\omega s^E T^2}{Q_M}$ $(1000 W cm^{-3})$

dielectric dissipation: $P_{DE} = \omega E^2 \epsilon_{33}^T \tan\delta$

mechanical losses: $P_{DM} = \omega E^2 k_{33}^2 \epsilon_{33}^T Q_M (1 - \eta)$

where $Q_M$ is overall transducer $Q$ and $\eta$ is the efficiency.
$\eta \approx 97\%$ [Berlincourt et al 1964]

for PZT-4 1 cm cube at resonance: $3.5\ W cm^{-3}$ $(500 W kg^{-1})$

# Reinforcement Learning

Learning algorithms for problems in a Markov decision process framework:

states $\mathbf{s} \in \mathcal{S}$

actions $\mathbf{v} \in \mathcal{V}(\mathbf{s})$

transition probabilities $p(\mathbf{s_i}, \mathbf{v}, \mathbf{s_j}) = \mathbf{p_{i,j}}(\mathbf{v})$

transition costs $c(\mathbf{s_i}, \mathbf{v}, \mathbf{s_j}) = \mathbf{c_{i,j}}(\mathbf{v})$

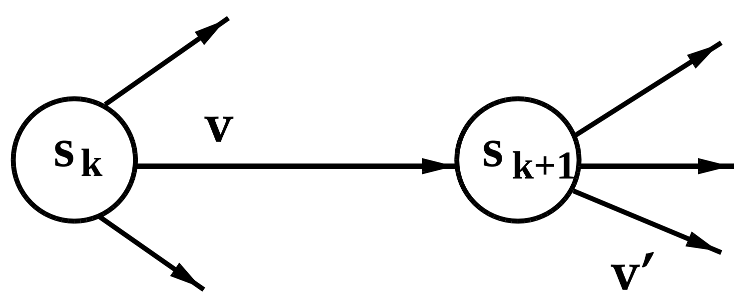
Algorithms learn the *minimum expected cost-to-go* or *value* of each state and thus can determine the best *policy* (choice of action in each state)

# $Q$ Learning

$Q(\mathbf{s_k}, \mathbf{v}) \equiv$ the expected cost-to-go when action $\mathbf{v}$ is chosen in state $\mathbf{s_k}$ and optimal actions are chosen thereafter.

The optimal $Q$ function, $Q^*(\mathbf{s_k}, \mathbf{v})$, is a fixed point of the Bellman equation:

$$Q^*(\mathbf{s_k}, \mathbf{v}) = E\left[c_{k,k+1}(\mathbf{v}) + \min_{\mathbf{v}'} Q^*(\mathbf{s_{k+1}}, \mathbf{v}')\right]$$




Controller Learning: “learning by watching” or “learning by doing”