Uncovering signals from measurement noise by electro mechanical amplitude modulation

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Abstract. We present an electromechanical parametric scheme to improve the low-frequency signal-to-noise ratio of energy buffering type transducers. The method is based on periodic modulation of the stiffness in the sensory system which produces upconverted replicas of the signals of interest at frequencies where measurement is less troubled by noise or other detrimental effects. We demonstrate this principle by means of capacitive biomimetic hair flow sensors, where we modulate the rotational spring stiffness by periodic electrostatic spring softening, such that a replica of the original signal is formed around the modulation frequency. Using this replica we gain up to a 25-fold improvement of the low-frequency signal-to-noise ratio and sensing threshold. For transient measurements we demonstrate that tiny signals, which are below the noise-levels in the base-band, are revealed well when upconverted to higher frequencies.
1. Introduction

Biology displays a variety of sensory mechanisms that constitute exceptional sensory performance, e.g. with respect to sensitivity, dynamic range, frequency filtering and selectivity. Auditory sensing systems in nature may exhibit mechanical filtering and amplification (White and Grosh 2005), whereas flow sensing systems may make use of noise to enhance their sensing capabilities (Levin and Miller 1996). Such systems and their natural implementation form a rich source of inspiration to engineers. Despite advancements in engineering and technology throughout history, it is still challenging for engineered systems to compete with biological systems. For example, the auditory capabilities of bats to perceive their environment, locate prey and to navigate at high velocities through complex surroundings (e.g. with leafed brushes and trees) (Schnitzler et al 2003) has no engineered equivalent.

Crickets are capable of sensing low-frequency sound by using mechanoreceptive sensory hairs to obtain information about the environment and avoid, e.g. predator attacks. These so-called filiform hairs, which are situated on the back of the cricket’s body on appendices called cerci, are able to sense air flows with velocity amplitudes down to $30 \mu m s^{-1}$ (Shimozawa et al 1998) and operate around the energy levels of thermal noise (Shimozawa et al 2003). Each hair is lodged in a socket, guiding the hair to move in a preferred direction. When subjected to air flow, the neuron is fired upon rotation of the hair base (figure 1). Indicatively, for wood crickets (Nemobius sylvestris) the hairs vary in length up to around 1 mm, with a bimodal distribution with concentrations around 150 and 750 $\mu m$ (Dangles et al 2005). These hair dimensions allow, in principle, for biomimicry by a technology generally denoted as micro electro mechanical systems (MEMS). Taking these hair-sensors as a source of inspiration,
several research groups have worked on the development of artificial counterparts for air flow measurements by exploiting MEMS technology.

Measurement of dc air flows using hair-sensor inspired flow sensors was shown by Ozaki et al (2000). They realized artificial hair-sensors by fabrication of cantilevers with read-out by strain gauges, and measured flow velocities ranging from tens of cm s$^{-1}$ up to 2 m s$^{-1}$. Other groups (Tao and Yu 2012) also developed cantilever-based structures with strain gauges for measurement of dc air flows, and showed measurements of flow velocities ranging from 0.7 mm s$^{-1}$ up to 20 m s$^{-1}$ (Chen et al 2007) and up to of 45 m s$^{-1}$ (Wang et al 2007). Sadeghi et al (2011) fabricated an artificial hair flow sensor by manually mounting a hair on a hydraulic sensor-system, for conversion of angular rotation into capacitive changes, capable of measuring dc-flows from (theoretically) 3 mm s$^{-1}$ up to 10 m s$^{-1}$.

In contrast, hair-sensor inspired flow-sensors for measurement of (tiny) ac air flows have been designed and fabricated in our group (Dijkstra et al 2005). Evolved fabrication methods and designs (figure 2) have led to electronic-noise limited performance, enabling the detection and measurement of flow velocities in the range of sub-mm s$^{-1}$ while retaining a bandwidth on the order of 1 kHz (Bruinink et al 2009). Additionally, we have demonstrated the use of arrays of hair-sensors (Dagamseh et al 2010) and their suitability as so-called ‘flow cameras’ (Dagamseh et al 2012). Exploiting the electrostatic transduction-nature of our cricket-inspired sensory system we have demonstrated that the flow sensitivity can be enhanced by more than 80%, at the cost of a slightly reduced bandwidth (Droogendijk et al 2012). Similarly, non-resonant parametric amplification has been implemented to improve the responsivity to incoming air flow by up to 20 dB while having large selectivity with respect to non-frequency-matched signals (Droogendijk et al 2011).

In this work, we exploit parametric effects to implement electromechanical amplitude modulation (EMAM) in order to improve the flow sensitivity at low frequencies. Previously, Raskin et al (2000) fabricated a MEMS-device as part of an electrical circuit, in which they exploited parametric amplification by electromechanical frequency-upconversion of the electrical input signal. Trusov and Shkel (2007) applied the technique of EMAM in a micromachined gyroscope, in order to separate the motional signal from the parasitic feed-through of the applied drive voltages. However, they achieved their upconversion by electrostatically driving their device rather than exploiting parametric mixing of frequencies. Here, we demonstrate EMAM by upconversion of low-frequency air flow signals to
higher frequencies using parametric frequency mixing, achieving improved sensor detection thresholds.

The organization of this paper is as follows. Section 2 starts with a theoretical model of the hair flow sensor, followed by the principle of stiffness control using electrostatic forces. Then, the concept of EMAM is introduced, where analytical modelling by harmonic balancing is compared to numerical simulations. Experiments for both harmonic and pulse-like flows are described in section 3. In section 4, several aspects of EMAM are discussed, like the benefits and its applicability to other domains.

2. Theory and modelling

A simple picture of the EMAM scheme discussed in this paper is the following. If in a mechanical system a spring-stiffness can be modulated as a function of time, this will result in temporal variations in response when the spring is subjected to a certain loading. For example, with a constant load its response will vary in time according to the spring modulation. Obviously, without loading the response will be zero. Hence, the response to the combined effects of loading and spring-stiffness modulation will consist of the product of loading times the spring-stiffness variation and therefore the response to the loading has a frequency-shifted component.

To illustrate the principle of EMAM, consider the frequency spectrum shown in figure 3. Here, a signal with information containing frequencies between 0 and $\omega_a$ is present. By harmonically modulating the system’s torsional stiffness, the information is upconverted to frequencies around the stiffness modulation frequency $2\omega_p$. As a result, the flow information is shifted to frequencies between $2\omega_p \pm \omega_a$. Furthermore, the transfer of a mechanical second order system with resonance frequency $\omega_r$ is shown by a red line. Figure 3 indicates that the
Figure 3. Illustration of the principle of EMAM.

Figure 4. Model of a flow sensing hair based on an inverted pendulum (Shimozawa et al 1998).

upconverted frequencies should not substantially exceed the system’s resonance frequency in order to remain a faithful representation of the original information.

Generally, EMAM can be used to shift signal-responses to frequencies that are favourable with respect to the signal-to-noise ratio (SNR). In the following we will give the theoretical basis for the application of this scheme to our rotational hair-based flow-sensors.

2.1. Hair mechanics

Mechanically, the hair flow sensor can be understood as a so-called inverted pendulum (figure 4); a second-order rotational-mechanical system with moment of inertia $J$ due to the hair, a rotational stiffness $S$ and a rotational damping $R$. The air flow generates a drag-torque $T(t)$ on the hair-shaft, mostly by viscous drag (Stokes 1851) at the velocities and geometries.
Controlling the torsional stiffness by applying ac-bias voltages to the sensor capacitances.

Figure 5. Controlling the torsional stiffness by applying ac-bias voltages to the sensor capacitances.

normally encountered, resulting in a description of the system’s response by

\[ J \frac{d^2 \theta(t)}{dt^2} + R \frac{d\theta(t)}{dt} + S(t)\theta(t) = T_0 \cos(\omega_a t). \]  

(1)

In fact \( R \) and \( J \) in (1) contain added contributions from the hair movement relative to the air which we do not discuss here (see e.g. Humphrey et al (1993)). To exploit parametric effects in the hair-based flow sensor, the torsional stiffness \( S(t) \) in (1) can be controlled by a time-dependent voltage.

2.2. Stiffness modulation

The electrostatic transduction nature of the system is used to induce balanced electrostatic forces by voltages symmetrically applied to the electrodes (figure 5). The resulting torque and stiffness can be calculated from the capacitor geometry. The capacitor is treated as a parallel plate capacitor (figure 6) with width \( w \), total length \( 2L \) and mutual plate distance \( g \). The sensor operates in air, for which the relative electric permittivity \( \epsilon_r \) is assumed to be equal to 1. Additionally, the silicon-nitride layers increase the effective dielectric distance to the gap given by \( t_{SiN}/\epsilon_r, SiN \), leading to an effective gap \( g_{eff} \):

\[ g_{eff} = \frac{t_{SiN, top}}{\epsilon_r, SiN} + g + \frac{t_{SiN, bottom}}{\epsilon_r, SiN}. \]  

(2)

The angle dependent capacitance \( C \) for the rotational sensor is given by

\[ C = \int_{-L}^{L} \frac{\epsilon_0 w \cos(\theta)}{g_{eff} - x \sin(\theta)} \, dx, \]  

(3)

where \( x \) is the direction parallel to the plates and \( \theta \) is the angle of rotation of the upper plate. Transduction principles are used to find the electrostatic spring softening by an angle-dependent and voltage-controlled capacitor. Applying an ac-bias voltage with amplitude \( U_p \), angular frequency \( \omega_p \) and phase \( \phi_p \) yields the total torsional stiffness \( S(t) \):

\[ S(t) = S_0 - \frac{1}{4} U_p^2 \frac{\partial^2 C}{\partial \theta^2} - \frac{1}{4} U_p^2 \cos(2\omega_p t + 2\phi_p) \frac{\partial^2 C}{\partial \theta^2}. \]  

(4)
This result shows that the torsional stiffness $S$ is dependent on the parameters of the applied ac-bias voltage, further referred to as the pump voltage $U_p$. The expression states that, under the small rotational angles normally encountered, the total torsional stiffness contains the intrinsic material-based stiffness $S_0$, a time-independent softening term and a frequency and phase-dependent softening term.

In the above analysis we have identified a convenient method to produce temporal modulations of the spring-constant in our hair-sensor system. These temporal spring modulations will drive the signals at higher frequencies, as will be derived in the next subsection.

2.3. Electro mechanical amplitude modulation (EMAM)

To achieve EMAM in our hair flow sensory system, an air flow with frequency $\omega_a$ together with the pump set at a much higher frequency $\omega_p$ is required. As a consequence of parametric frequency mixing—the interaction between flow response and pump induced spring-stiffness variations at twice the pump frequency—the flow information will not only be present at the frequency $\omega_a$, but also at the frequencies $2\omega_p \pm \omega_a$ (see also figure 3).

To find an analytical approximation for the amplitude of the frequency components at which the flow information is present after this upconversion, the method of harmonic balancing (Harish et al 2009) is used. By balancing terms containing $\pm \omega_a$ and $\pm (2\omega_p \pm \omega_a)$, and truncating the series for higher order terms, the rotational angle amplitudes for the retained frequencies are found.

Consider the second order differential equation from (1) describing the hair sensor’s mechanics. For convenience, the air flow induced torque $T(t)$ and time-dependent torsional stiffness $S(t)$ can be expressed as

$$T(t) = \frac{T_0}{2} [e^{j\omega_a t} + e^{-j\omega_a t}], \quad S(t) = S_0 - \frac{1}{2} \frac{\partial^2 C}{\partial \theta^2} u(t)^2. \quad (5)$$

The ac-bias voltage is a harmonic voltage with amplitude $U_p$, phase $\phi_p$ and frequency $\omega_p$:

$$u(t) = \frac{U_p}{2} [e^{j(\omega_p t + \phi_p)} + e^{-j(\omega_p t + \phi_p)}].$$

Squaring the expression for $u(t)$:

$$u(t)^2 = \frac{U_p^2}{2} + \frac{U_p^2}{4} e^{2i\phi_p} e^{2j\omega_p t} + \frac{U_p^2}{4} e^{-2i\phi_p} e^{-2j\omega_p t}. \quad (6)$$

As a result, the torsional stiffness $S(t)$ can be expressed as

$$S(t) = S_0 - \frac{1}{2} \eta U_p^2 - \frac{1}{4} \eta U_p^2 e^{2j\omega_p t} - \frac{1}{4} \eta U_p^2 e^{-2j\omega_p t} \quad (7)$$
in which the phase-dependency is suppressed ($\omega_a \neq \omega_p$), and \( \eta \) represents a geometrical constant:

\[
\eta = \frac{1}{2} \frac{\partial^2 \mathcal{C}}{\partial \theta^2} \approx \frac{2 \varepsilon_0 w L^3}{3 g_{\text{eff}}^2}.
\]

This result shows that the net torsional stiffness \( S(t) \) contains four terms: two that are frequency-independent, one at frequency \( 2\omega_p \) and one at frequency \(-2\omega_p \).

Since the driving torque is at \( \pm \omega_a \), \( \theta(t) \) will contain these frequencies. Due to the product of \( S(t) \), given by equation (7), and \( u(t)^2 \), given by equation (6), the rotational angle amplitude \( \theta(t) \) will also contain frequency components at \( 2\omega_p \pm \omega_a \):

\[
\theta(t) = \theta_1 e^{j\omega_p t} + \theta_2 e^{-j\omega_p t} + \theta_3 e^{j(2\omega_p - \omega_a) t} + \theta_4 e^{-j(2\omega_p - \omega_a) t} + \theta_5 e^{j(2\omega_p + \omega_a) t} + \theta_6 e^{-j(2\omega_p + \omega_a) t}.
\]

where higher frequencies are neglected. This system of equations can be approximated as a linear system of coupled differential equations, one for each of the frequencies in (9). The differential equations are given by

\[
-\omega_a^2 J \frac{\partial}{\partial t} \theta_i + j \omega_i R \theta_i + [S(t) \theta(t)]_{\omega_i} = \frac{T_0}{2} \left[ \delta(\omega_i - \omega_a) e^{j\omega_p t} + \delta(\omega_i + \omega_a) e^{-j\omega_p t} \right].
\]

\([S(t) \theta(t)]_{\omega_i}\) implies the terms at frequency \( \omega_i \). The Kronecker delta function (\( \delta \)) restricts the driving to the frequency of the air flow (\( \omega_a \)). For convenience, we introduce the shorthand notations:

\[
a = \frac{1}{4} \eta U_p^2, \quad b = S_0 - 2a, \quad c = \frac{T_0}{2}.
\]

Furthermore, we define the frequencies

\[
\omega_1 = \omega_a, \quad \omega_3 = 2\omega_p - \omega_a, \quad \omega_5 = 2\omega_p + \omega_a,
\]

\[
\omega_2 = -\omega_1, \quad \omega_4 = -\omega_3, \quad \omega_6 = -\omega_5.
\]

Additionally, we define for the frequency-dependent terms involving \( J \) and \( R \):

\[
g(\omega) = -\omega^2 J + j \omega R \quad g_i = g(\omega_i).
\]

On collecting terms at equal frequencies and neglecting frequencies higher than \( 2\omega_p + \omega_a \), we find

\[
\begin{align*}
@ \omega_1 & : \quad g_1 \theta_1 + b \theta_1 - a \theta_4 - a \theta_5 = c, \\
@ \omega_2 & : \quad g_2 \theta_2 + b \theta_2 - a \theta_3 - a \theta_6 = c, \\
@ \omega_3 & : \quad g_3 \theta_3 + b \theta_3 - a \theta_2 = 0, \\
@ \omega_4 & : \quad g_4 \theta_4 + b \theta_4 - a \theta_1 = 0, \\
@ \omega_5 & : \quad g_5 \theta_5 + b \theta_5 - a \theta_1 = 0, \\
@ \omega_6 & : \quad g_6 \theta_6 + b \theta_6 - a \theta_2 = 0.
\end{align*}
\]

Note that the equations at \( (\omega_1, \omega_4, \omega_5) \) are decoupled from those at \( (\omega_2, \omega_3, \omega_6) \). For the amplitude \( \theta_1 \) at the flow frequency \( \omega_1 \) we find

\[
@ \omega_1 : \quad \theta_1 = c \frac{1}{g_1 + b - a^2 \left[ \frac{1}{g_4 + b} + \frac{1}{g_5 + b} \right]}.
\]
Table 1. Parameter values of the hair mechanical system and the capacitor.

| Quantity            | Symbol | Value            |
|---------------------|--------|------------------|
| **Mechanical parameters** |        |                  |
| Torsional stiffness | $S_0$  | $9.5 \times 10^{-9}$ Nm rad$^{-1}$ |
| Torsional resistance | $R$    | $1.2 \times 10^{-12}$ N m s rad$^{-1}$ |
| Moment of inertia   | $J$    | $3.1 \times 10^{-16}$ kg m$^2$ |
| **Sensor specifications** |        |                  |
| Quality factor      | $Q$    | 1.43             |
| Resonance frequency | $f_0$  | 881 Hz           |
| **Hair geometry**   |        |                  |
| Hair length         | $L_h$  | 800 $\mu$m       |
| Hair diameter       | $d_h$  | 50 $\mu$m        |
| **Capacitive structures** |      |                  |
| Membrane length     | $L$    | 95 $\mu$m        |
| Membrane width      | $w$    | 90 $\mu$m        |
| Gap distance        | $g$    | 850 nm           |
| Nitride thickness   | $t_1$  | 1000 nm          |
| Nitride thickness   | $t_2$  | 200 nm           |
| Relative permittivity | $\varepsilon_r$ | 7.5              |

The resulting amplitude for the frequencies containing the flow information by EMAM

$$\theta_4 = c \frac{a}{g_4 + b} \left[ \frac{1}{g_1 + b - a^2} \left( \frac{1}{g_4 + b} + \frac{1}{g_5 + b} \right) \right]$$ (16)

and

$$\theta_5 = c \frac{a}{g_5 + b} \left[ \frac{1}{g_1 + b - a^2} \left( \frac{1}{g_4 + b} + \frac{1}{g_5 + b} \right) \right].$$ (17)

The results for $\omega_2$, $\omega_3$, $\omega_6$ are the complex conjugated of the results for $\omega_1$, $\omega_4$, $\omega_5$, respectively. The derived expressions are explicit expressions with parameters that readily can be calculated using the short hand definitions and the values from table 1. It is noteworthy to mention that the amplitudes of $\theta_1$, $\theta_4$ and $\theta_5$ all depend linearly on $c$, representing the input air flow. Therefore, according to the above analysis it follows that the EMAM concept behaves linearly and is applicable to more complex input signals, like transients. However, the weak dependence on input frequency may cause some distortion of the input signal.

The rotation at $\omega_4$ or $\omega_5$ divided by the rotation at $\omega_1$ can be regarded the gain-factors $G$ at the respective frequencies due to the EMAM approach. They are given by

$$G_{1 \rightarrow 4} = \frac{a}{g_4 + b}, \quad G_{1 \rightarrow 5} = \frac{a}{g_5 + b}. \quad (18)$$

In the limit for $U_p \rightarrow 0$, $a$ will be 0 and therefore $\theta_4 = \theta_5 = 0$ and $\theta_1 = c/(g_1 + b)$ coinciding with the intrinsic mechanical response (i.e. without the use of bias-voltages). Conversely, the norm of the denominators in these expressions may be smaller than $a$ for proper combinations of $U_p$ and $\omega_i$, meaning that there can be a genuine gain of the signal. The conditions under
Figure 7. Frequency transfer comparison between the analytical model by harmonic balancing using terms $\omega_a$ and $2\omega_p \pm \omega_a$ (solid lines), harmonic balancing using terms $\omega_a$, $2\omega_p \pm \omega_a$, and $4\omega_p \pm \omega_a$ (dashed lines) and the numerical simulations (points) for various pump amplitudes with the flow frequency $f_a$ set to 10 Hz.

which a large gain may occur will in general be close to the conditions under which pull-in (i.e. instability) may take place, therefore requiring careful choice of the pump signal. Still, even at gain values below 1, there may be a considerable improvement of the SNR in case the noise level at the frequency of the upconverted signal is much lower than the noise level at the frequency of the original signal.

For comparison and validation, the outcome of the analytical results by harmonic balancing are compared to numerical simulations by the Runge–Kutta four method from MATLAB. Both results are shown in figure 7, using the parameters given in table 1. Also the impact of the addition of higher order terms with frequencies $4\omega_p \pm \omega_a$, following the same analysis by harmonic balancing, is shown. We observe that the simulations and analytical approximations by harmonic balancing are in good agreement. Generally, when the pump amplitude $f_p$ is increased, the rotation angle is increased, at the cost of a slightly reduced bandwidth.

Both simulations and model show that the pump frequency should not be chosen higher than about 500 Hz, since we observe that for higher frequencies the rotational angle $\theta_5$ rapidly decreases. Further, due to the quadratic nature of electrostatic forces, a pump frequency of 500 Hz coincides with a mechanical frequency of 1000 Hz, which is just slightly above the sensor’s resonance frequency (about 800 Hz).

To gain some more insight we may simplify the derived full expressions for $\omega_1$, $\omega_4$ and $\omega_5$, using the approximation that the upconverted flow information is at frequencies still sufficiently below the sensor’s resonance frequency, i.e. by letting $g_i \rightarrow 0$. As a result, we find

\[\begin{align*}
\text{at } \omega_1 : \theta_1 &= c \frac{b}{b^2 - 2a^2}, \\
\text{at } \omega_{4,5} : \theta_{4,5} &= c \frac{a}{b^2 - 2a^2}.
\end{align*}\]
By using the same approach for the frequencies \( \omega_2, \omega_3, \omega_6 \) and by resubstituting the various physical constants, we find for the rotational amplitudes

\[
\theta_{1,2} = \frac{T_0}{S_0} \frac{(1 - \lambda U_p^2)}{(\lambda U_p^2)^2 - 4\lambda U_p^2 + 2} \quad \text{with} \quad \lambda = \frac{\eta}{2S_0},
\]

(21)

\[
\theta_{3,4,5,6} = \frac{T_0}{2S_0} \frac{\lambda U_p^2}{(\lambda U_p^2)^2 - 4\lambda U_p^2 + 2} = \frac{\theta_{1,2} \lambda U_p^2}{2(1 - \lambda U_p^2)}.
\]

(22)

The geometrical and other properties of the capacitive structure, as well as the parameters of the hair flow sensory system, as used in the calculation of the theoretical response are listed in table 1.

Our numerical and analytical analyses indicate that we can use harmonic spring-stiffness variations to generate replica of the incoming flow signals at higher frequencies. In the next section we will describe the experimental findings and identify the benefits of the EMAM scheme.

3. Experimental

3.1. Setup

Experiments are performed using the setup shown in figure 8. A waveform generator (Agilent 33220A-001) is used to generate a sinusoidal signal at a frequency \( f_a \) that is applied to an amplifier. This amplifier drives a vibrating sphere to generate the oscillating air flow field described by a dipole source (Lamb 1932). A second waveform generator (Agilent 33220A-001) is used to supply the ac-pump voltage to the top electrodes. The bottom electrode is grounded as
Figure 9. The applied periodic air flow (30 Hz) using a vibrating sphere, the amplitude modulated membrane velocity and the synchronous detected flow signal (30 Hz) in the time-domain. The ac-bias voltage was set to 300 Hz with an amplitude of 3 V.

is the measurement setup. The sensor rotational angular velocity \( \dot{\theta} \) is derived from laser Doppler vibrometry using a Polytec MSA-400, since there is a simple factor between the measured membrane velocity and the hair rotational angular velocity \( \dot{\theta} \). The resulting vibrometer output voltage representing \( \dot{\theta} \) is fed to an adjustable band pass filter (Stanford SR 650). To demodulate the membrane velocity by synchronous detection the filtered output is supplied to a lock-in amplifier (Stanford SR 830) with its reference frequency set to twice the pump frequency.

3.2. Demonstration of EMAM

To demonstrate EMAM in our biomimetic hair flow sensors, the vibrating sphere was used to generate a periodic flow at 30 Hz. The amplitude of the ac-bias voltage was set to 3 V and its frequency to 300 Hz. As a result, by the quadratic nature of electrostatic actuation, the torsional stiffness is modulated at twice the frequency, 600 Hz. Figure 9 shows the measured (modulated) membrane velocity, together with the voltage applied to the vibrating sphere and the resulting signal after synchronous detection (at 600 Hz) using the lock-in amplifier.

We observe that with the use of EMAM the flow signal at 30 Hz produces an ac-modulated membrane rotation around 600 Hz (middle graph) largely reflecting the low frequency signal in the amplitude. There is an additional contribution from the vertical vibrations of the sensor’s membrane at 600 Hz but this component is suppressed in the demodulated membrane rotational velocity (lower graph), which clearly represents the incoming air flow.
Improving measurement quality

The output rms voltage of the vibrometer signal was measured for varying flow velocities (figure 10), still at a frequency of 30 Hz, both for the original flow signal (band-pass filter set to 25–35 Hz) and the demodulated EMAM signal (band-pass filter set to 565–635 Hz). The ac-bias voltage, at 300 Hz, was varied in amplitude from 3 to 6 V. The quality of the measurements at lower frequencies is significantly improved using EMAM. Without EMAM, the measured output voltage as a function of flow amplitude (see figure 10 lowest curve) is rather noisy. With EMAM a clear linear relationship is observed for flow velocity amplitudes above threshold.

We use the results of figure 10 to determine the lowest detectable (threshold) flow-amplitudes as a function of $U_p$. The output voltage is assumed to be proportional to the flow velocity amplitude $u_0$, given by a coefficient $S_c(U_p)$. Letting $N_{sc}$ be a constant representing the rms value of the additive, uncorrelated, noise power, the measured output voltage $U_{out}$ can be represented as (Droogendijk et al 2012)

$$U_{out} = \sqrt{(S_c u_0)^2 + N_{sc}^2}. \quad (23)$$

We define the flow threshold as the intersection of the two asymptotes of (23), given by $\text{SNR} = 1$, which is $N_{sc}/S_c$. The solid curves in figure 10 represent fits to the measurements according to (23) and yield the threshold flow-amplitudes.

Although a high pump amplitude $U_p$ potentially provides a significant improvement in flow sensitivity, the sensor response deteriorates for higher flow velocity amplitudes. The combination of finite vertical stiffness of the torsion beams, a strong pump and a large air flow...
results in displacements of the membrane in the order of tens of per cent of the gap distance $g$. As a consequence, these effects contribute to the system’s response, resulting in a nonlinear relationship between output rms-voltage and driving air flow (orange circles in figure 10).

Approximating the threshold velocity to be inversely proportional with the rotational angle, using (22), the comparison between model and measurements is made in figure 11. It demonstrates that (22) can be used well to describe the improvement in threshold reduction as a function of pump voltage $U_p$. We observe that increasing $U_p$ will cause the detection limit to decrease nonlinearly, but may also affect the stability of the system for high values of $U_p$. When $U_p$ reaches a critical value, the total torsional stiffness becomes zero causing pull-in instability, which is also predicted by the analytical model.

The measurements show that EMAM in the studied case reduces the detection limit by a factor of 25 (from 50 to 2 mm s$^{-1}$). At the same time it is obvious that improvement of the detection limit requires a certain minimum value for $U_p$, which is about 3 V in our case (intersection of plots in figure 11).

3.4. Application of EMAM to transient flows

Although the application of sinusoidal air flows simplifies modelling and enables quantitative investigation of EMAM, the use of transient signals with increased spatio-temporal flow information, is more akin to what one may want to measure in practice than sinusoidal flows. In nature, there are numerous examples representing transient air flow stimuli such as spider motion (Dangles et al 2006) and (passing) humming flies (Barth et al 1995). Furthermore, such stimuli appear to have most of their signal power present in the lower frequency range, emphasizing the requirement to have sufficient sensor responsivity at low frequencies (Kant and Humphrey 2009). Therefore, we also performed measurements on pulsed-like air flows.

Previously, we measured responses of our biomimetic hair flow sensors to air flow transients using a sphere with 3 mm radius attached to a piston system to represent the motion of a spider at a certain distance from the sensor (Krijnen et al 2013). Now, we use a similar sphere with 3 mm radius (figure 12) mounted on a moving piston (SMAC LCA25-050-15F).
As an experimental setup, the previously described setup for optical investigation of EMAM is used (figure 8).

The tiny sphere was used to generate a transient air flow, where the piston speed was set to 20 cm s$^{-1}$. The amplitude of the ac-bias voltage was set to 4 V and its frequency to 400 Hz. As a result, by the quadratic nature of electrostatic actuation, the torsional stiffness is modulated at twice the frequency, 800 Hz. The filter’s bandwidth was adjusted to 760–840 Hz. Furthermore, the time constant of the lock-in amplifier was set to 10 ms and its low pass filter to 24 dB per oct roll-off.

Figure 12 shows in succession the theoretical applied air flow according to Lamb (1932), the measured (modulated) membrane velocity, and the resulting signal after synchronous detection (at 800 Hz) using the lock-in amplifier. We observe that with the use of EMAM the transient air flow signal produces an ac-modulated membrane rotation. The demodulated membrane rotational velocity clearly represents the incoming air flow, proving that EMAM can also be used to perform measurements on more complex signals. In addition, without the application of EMAM, we were not able to obtain a representation of the applied pulsed-like air flow at all, emphasizing the advantage of EMAM under the given experimental conditions.

To explain the improvement in SNR while using EMAM, the spectrum of the resolved transient flow (figure 13) is shown in figure 14 (red solid line). We observe that the overall spectrum is in good agreement with the theoretical analysis of Kant and Humphrey (2009) for pulsed air flows, since most of the signal power is found in frequencies within a range of about 10–60 Hz.

Furthermore, the noise level of the measurement setup (green solid line) is higher than the flow-induced sensor response, thus entirely masking the air flow. However, in case of EMAM the flow-information is frequency upconverted (blue solid line) to frequencies around 800 Hz. Although the rotational angle amplitudes are lower than compared to the case without EMAM, we observe also that the SNR at these higher frequencies is clearly larger than one. Therefore, by applying EMAM it is possible to measure low-frequency air flows which are normally covered in noise.
Clearly, the experimental data supports the notion that application of EMAM can be beneficially used to improve SNRs of harmonic signals and even uncover transient signals from measurement noise. In the next section we will discuss the conditions under which these improvements can be obtained and the applicability to other sensor systems.

4. Discussion

4.1. Noise analysis

To explain why EMAM can be used to enhance the measurable flow velocity range and/or the quality of the measurements, the origin of the noise sources needs to be discussed. A schematic of the system is shown in figure 15, which contains the flow signal $S_f(\omega)$, the sensor’s thermal mechanical noise $N_{th}$, the mechanical transfer of the sensory system $H(\omega_a, U_p)$, the transfer by EMAM $E(\omega_a, \omega_p, U_p)$, the applied voltage $u(U_p, \omega_p)$, the transfer of the measurement system $L(\omega)$, filtering of the measurement signal $F(\omega)$ and other noise sources $N_{sc}(\omega)$ independent of the sensory system.

In case of dominant non-flow related noise sources $N_{sc}(\omega)$, with larger power spectral density at $\omega_a$ than at $2\omega_p \pm \omega_a$ (e.g. in case of $1/f$ noise), and/or in case the transfer function $L(2\omega_p \pm \omega_a)$ mediates larger transfer than $L(\omega_a)$, the required air flow to achieve a detectable hair-rotation can be lower at $2\omega_p \pm \omega_a$ than at $\omega_a$. In these cases EMAM can help to achieve a better low-frequency detection limit by upconverting the information to higher frequencies.
Figure 14. Illustration of the advantage of EMAM for low-frequency flows. Originally, the signal spectral density is well below the noise floor of the measurement setup. On application of EMAM with a pump frequency of 400 Hz, the transient flow spectrum is upconverted to frequencies around 800 Hz. At these frequencies the SNR of the transient flow is clearly larger than one, enabling detection of the pulsed air flow.

Figure 15. Schematic view of the system for identification of the system’s noise sources. The upper path (red) illustrates the case without EMAM, the lower path (blue) shows the impact of EMAM.

To explain our achieved improvement in flow measurement on application of EMAM, the noise spectrum of the experimental setup only (thus without flow) is measured (figure 16) and related to the sensor’s rotational angle $\theta$. The spectrum exhibits a typical $1/f$ characteristic, meaning less signal is required at higher frequencies to achieve a suitable SNR. The spectrum shows peaks at multiples of 10 Hz, which affects flow measurements performed at these frequencies. Also the noise level of the Polytec MSA-400 system, which is specified as $< 1 \mu m s^{-1}$ (Polytec 2005), is given in figure 16 (green solid line). We observe that the measured output noise level is just below the specified noise level (green dashed line), suggesting...
that the output signal is dominated by the measurement equipment of the Polytec MSA-400 system.

To compare, the overall noise angle is significantly larger than expected based on thermal mechanical noise calculations (Droogendijk et al 2012), also shown in figure 16 (magenta solid line). Therefore, the output noise is dominated by non-flow related noise contributions and for this situation EMAM improves the detection limit and measurement quality of low frequency air flows.

4.2. Influence of higher frequency components

One may question why a relative small number of frequency components as used in the derivation of equations (15)–(17) delivers results so accurately reproducing the EMAM numerical and experimental results. It can be readily shown that the next four frequency terms that can be added to equation (14) depend on $a^2$. Since normally $a \ll 1$ these higher frequency terms are much smaller and play only a minor role for $\theta_4$ and $\theta_5$. These amplitudes, which are proportional to $a$ in the derived expressions (15)–(17), now get an additional contribution proportional to $a^3$. Additionally, these contributions have denominators $[(g_5+b)(g_9+b) - a^2]$ times larger, resulting in even lower contributions for most values of $\omega_p$ and $a$. Therefore, for all situations, except those close to pull-in instability, the higher frequency terms are of no concern, which is in agreement with the comparison between numerical simulations and harmonic balancing in figure 7.

4.3. EMAM with electronic read-out

In normal operation of our hair-sensors we use differential-capacitive electronic read-out (Bruinink et al 2009, Dagamseh et al 2010, 2012), whereas here we have shown the concept of EMAM using optical read-out by vibrometry. The reason we did not use the electronic read-out in our EMAM experiments is that the pump voltages used tend to saturate the electronics, since they are orders of magnitude larger than the tiny signals generated by the capacitive modulation. However, we believe this is no fundamental problem but can be solved by either
using electronics with larger dynamic range, or applying a sharp filter at $2\omega_p$ in the electronics. As far as the improvement by EMAM due to noise in the read-out electronics is concerned, the improvement will depend on the character of the electronics noise. For $1/f$ type dominated noise, comparable improvement as shown here is expected.

4.4. Extension of the concept

The theory we have used to derive the expressions for the EMAM amplitudes has been based entirely on the nature of energy buffering transducers. In more detail, an equivalent form of equation (4) can be derived for any energy buffering transducer, thus not only electrostatic, but also piezo-electric, electromagnetic and other types of energy buffering transducers. Therefore, we argue that EMAM has a wide application potential, especially with respect to low-frequency sensing. That is, it may for example be beneficial for gravity gradiometry, be applied in seismometers, in highly sensitive accelerometers and other comparable sensors and measurement systems.

5. Conclusions

Concluding, EMAM has been applied to biomimetic hair flow sensors. Using harmonic electrostatic spring softening, by application of an appropriate sinusoidal voltage on the capacitor plates, upconversion of the flow information is achieved. It is demonstrated that EMAM can improve the measurement performance at low frequencies, in case of limitations within the measurement setup. We have shown that the method can be applied equally well to transients as to harmonic signals. In the latter case we have presented improvements in threshold limits of up to 25 times, whereas in the transient measurements it was demonstrated that tiny signals, which were below the noise-levels in the base-band measurement, could be revealed well when upconverted to higher frequencies. We have argued that the method is not restricted to our sensors but can be generally applied to energy buffering transducers.

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