A Multiaperture Bioinspired Sensor With Hyperacuity

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Abstract—We have developed a multiaperture sensor based on the visual system of the common housefly (Musca domestica). The Musca domestica insect has compound eyes, which have been shown to exhibit the ability to detect object motion much finer than their photoreceptor spacing suggests, a phenomenon often called motion hyperacuity. We describe how such motion hyperacuity can be achieved through a controlled preblurring of an optical imaging system. We used this method to develop a software model of a new fly eye sensor and to optimize its motion hyperacuity. Finally, we compare the completed sensor to previously developed fly eye sensors. The new design shows a threefold improvement in signal-to-noise ratio and motion acuity.

Index Terms—Hyperacuity, insect vision, machine vision, multiaperture image sensor, sampling methods, visual system.

I. INTRODUCTION

The vast majority of imaging systems are inspired by human vision. They typically consist of a charge coupled device (CCD) or a complementary metal oxide semiconductor (CMOS) array behind a lens (or lens system) in a single-aperture design. Traditional imaging sensors are intuitive for humans and well-suited for many computer vision tasks. However, these sensors must transfer an enormous amount of information to a host processor. This is typically done via a serial connection, which limits the temporal resolution of the imaging device. Because of these drawbacks, a sensor based on the Musca domestica multiaperture visual system shows great promise for certain applications, such as edge and motion detection.

Insects have the ability to detect object motion over much smaller distances than their photoreceptor spacing suggests, a phenomenon known as motion hyperacuity [1]. In addition, the fly brain is incredibly simple when compared to that of the human. However, the fly is able to perform complicated image processing tasks, including object recognition, motion detection, and obstacle avoidance [2]. The fly is able to carry out all these tasks in real-time. It meets the real-time requirements by preprocessing the visual data in a parallel and analog fashion [3].

When we discuss hyperacuity in this paper, we refer to the concept of motion hyperacuity defined by Nakayama [1]. Motion hyperacuity occurs when a stationary imaging system is able to detect object motion much finer than the photoreceptor spacing would suggest. This is not to be confused with other studies which have measured static hyperacuity [4]–[8] (i.e., a subpixel resolution of line pairs) or vernier hyperacuity [9] with a scanning sensor, relying on active visual processes.

This paper presents the design of a new sensor inspired by the anatomy of the common housefly. We describe how motion hyperacuity can be achieved in such an imaging system. We then show how we used optical modeling to optimize the newly designed sensor. Finally, we compare the performance of the new sensor to previously designed “fly eye” sensors.

II. BACKGROUND

Traditional CCD or CMOS imaging sensors are inspired by the single aperture “camera eye” design seen in the anatomy of the human eye. However, the sensor described in this paper is inspired by the visual system of the common housefly, Musca domestica. At first glance, the fly’s eye appears to be a much poorer imaging system. It suffers from small aperture optics which leads to a broad Gaussian photoreceptor response [10]–[12] (technically speaking, the response has the form of an Airy disk, but a Gaussian approximation is commonly used). This causes the fly to have poor resolution in the traditional sense (i.e., the ability to resolve line pairs). The fly’s spatial resolution [also known as the minimum angle of resolution (MAR)] is roughly 2°/5 [13], compared to the MAR of the human eye, which is approximately 1°/60 for 20/20 vision [14].

The Musca domestica has two compound eyes, each consisting of about 3000 facets called ommatidia. Each ommatidium is, in itself, a crude imaging system. It consists of a focusing lens (the cornea), a cone shaped lens, and eight receptors (the rhabdomeres, usually designated R1–R8) [10]. Each rhabdomere has been shown to exhibit an approximately Gaussian response [15]–[17]. The anatomy of an ommatidium is depicted in Fig. 1.

The Musca domestica isolates the light in each individual rhabdomere. The signals of the R1–R6 rhabdomeres from spatially adjacent lenses are combined in the L1 and L2 neurons in the lamina (shown as the shaded parts in Fig. 1). These rhabdomeres share a single optical axis. This slightly shifted field-of-
view is how the phenomenon of motion hyperacuity is achieved. The R7 and R8 rhabdomeres, which are nearly coaxial in the ommatidium, are routed directly to the medulla and do not contribute to the neural superposition effect [3]. We concentrate here on the rhabdomeres whose signals are combined in the same L1 and L2 neurons and share a common optical axis.

Researchers at the University of Wyoming have developed sensors mimicking certain aspects of the visual system of the Musca domestica [18]–[22]. The two most recent sensor designs are depicted in Fig. 2. These designs were both shown to exhibit motion hyperacuity [18], [21].

A number of sensors based on the compound eye have been developed at other institutions. Perhaps the earliest was first imagined by Angel in 1979 [23]. He presented a design of a new X-ray telescope based on the lobster’s multiaperture visual system. The greatest advantage was that the proposed telescope had a (180°) field-of-view. However, its main drawback was that the spatial resolution did not improve upon state of the art telescopes [24]. Thus, the telescope was never fully realized.

Since 1980, a number of compound eye sensors have been developed [11], [25]–[28]. Each of these sensors are based on the apposition compound eye, rather than a true neural superposition compound eye. The goal of each of these sensors is to develop an apposition sensor that achieves a type of static hyperacuity (it can localize points and edges to a fraction of its photoreceptor spacing) [29]. A comprehensive literature search indicates that, while many people have studied the design and construction of compound eye sensors, researchers at the University of Wyoming (UW) are unique in developing compound eye sensors for motion detection and motion hyperacuity using off-the-shelf components.

Note that collaborative efforts between UW and Wilcox et al. at the U.S. Air Force Academy have also explored other “fly-eye” sensor construction aspects [30].

III. PREBLURRING AND HYPERACUITY

To simplify the presentation, we consider only the $x$ direction; the $y$ direction would follow the same analysis. In order to evaluate the effects of preblurring, the response of adjacent pixels, spaced $X_s$ apart, must be observed. Let the input image, $f(x)$ be the equivalent of an impulse (or Dirac delta) function (optically speaking, an infinitesimal point-of-light) centered over the $n$th pixel, $\delta(x - nX_s)$. The response of the $n$th pixel to such an impulse is $h(x - nX_s)$. This assumes perfect optics, so that the incoming point of light is not spread (or smeared) by the point spread function (PSF) of imperfect optics. If the incoming image is spatially shifted by some $\Delta x$, then the response of the $n$th pixel changes by

$$\Delta h(x - nX_s) = h(x - nX_s - \Delta x) - h(x - nX_s).$$  \hspace{1cm} (1)

It follows that motion can only be detected if

$$\Delta h(x - (n + 1)X_s) - \Delta h(x - nX_s) > \epsilon$$  \hspace{1cm} (2)
depends on the noise floor and contrast limit of the system, as can be seen in Fig. 3. Note that behind the lens, the inter-lens angle is usually assumed, is chosen to be the focal length of the lens. Then, is limited by the size of the photodetector. Thus, the blurring. In this case, the width of the PSF due to the optics must be taken into account. First, consider the case with minimal preblurring. As shown in Fig. 3, the adjacent pixel responses in an unblurred system [31].

\[
\Delta h(x - nX_s) = \frac{d}{dx} h(x) \big|_{x=X_s} 
\]

where \( \epsilon > 0 \) depends on the noise floor and contrast limit of the system.

Now, we assume realizable optics where the associated PSF must be taken into account. First, consider the case with minimal blurring. In this case, the width of the PSF due to the optics is less than the width of an individual photodetector. Thus, the shape of \( h(x) \) will be dominated by the photodetector weighting function (typically considered to be a rect function). This results in large constant areas of \( h(x) \), as can be seen in Fig. 3. Note that the shift by a small \( \Delta x \) results in negligible differences in pixel responses (i.e., \( \Delta h(x - (n+1)X_s) - \Delta h(x - nX_s) \approx 0 \)). In fact, \( \Delta x \) must approach \( X_s \) before any motion is detected. This is similar to human vision, where a shift of approximately \( X_s/5 \) must occur before motion can be detected [1].

Now, consider the case with a specific amount of preblurring, where the PSF is wider than the width of an individual photodetector (see Fig. 4). In this situation, the shape of \( h(x) \) is dominated by the shape of the PSF, and it appears to be Gaussian. In theory, since there are no constant regions in \( h(x) \), all motion is detectable, no matter how small. However, this is not true in practical applications. The ability to detect motion is limited by the noise floor of the system and the contrast limit, represented by \( \epsilon \) above.

While such preblurring can be used to achieve motion hyperacuity, more blurring does not necessarily yield better motion acuity. Excessive blurring leads to a more uniform PSF and thus less motion acuity. Therefore, \( h(x) \) can be tailored to maximize motion acuity. It follows from (2) that this happens when \( \frac{d}{dx} h(x) \big|_{x=X_s} = \frac{d}{dx} h(x) \big|_{x=0} \) is maximized. Since symmetry of \( h(x) \) is usually assumed, \( \frac{d}{dx} h(x) \big|_{x=0} = 0 \). Then, hyperacuity is best achieved when the following is maximized [31]:

\[
\frac{d}{dx} h(x) \big|_{x=X_s}.
\]

**IV. SOFTWARE MODEL**

We used a software model to design a sensor that maximized motion hyperacuity, using the ZEMAX optical design package [32]. We chose a multiperture design because it allowed us to separate the optimization into two parameters: the shape of the pixel response \( h(x) \) and the spatial sampling period \( X_s \). In a single aperture design, \( X_s \) is limited by the size of the photodetector and motion acuity is determined solely by the degree of preblurring.

Fig. 5 shows the salient aspects of the new sensor design. It is a nonplanar, multiperture design. While the design does not exactly mimic the fly eye (we use only one photodetector per lens rather than 8), it still boasts many of the same beneficial characteristics. The design consists of a series of lenses (3 mm diameter, 2.6 mm focal length), each focusing light onto a single optical fiber. The multimodal fiber has core diameter of 1 mm, jacket diameter of 2.2 mm, and numerical aperture of 0.5. The fiber sits at a distance \( w \) behind the lens. The inter-lens angle \( \Delta \varphi \) is also shown in the figure. Motion hyperacuity can be optimized for this sensor configuration by simply adjusting the two parameters, \( w \) and \( \Delta \varphi \).

The first task in maximizing the motion acuity of the sensor was to optimize the response of a single photoreceptor. This was done by adjusting the distance between the lens and the image plane \( w \) in Fig. 5. If \( w \) is chosen to be the focal length of the lens, then the light is most focused (i.e., minimal preblurring). As \( w \) deviates from the focal length, the light on the fiber becomes increasingly blurred.

Obviously, the greater a response each photoreceptor has to incoming light, the easier it is to detect motion. However, optimizing the response is not as simple as maximizing the peak. A Gaussian shape must be maintained so that there are no “flat” regions in the response (motion cannot be detected in a region of constant response). Therefore, a heuristic method was used to determine optimal preblurring (the response with the highest peak that still appeared Gaussian was chosen as optimal). Fig. 6 shows three cases: insufficient preblurring (top dashed line), excessive preblurring (bottom dot-dashed line) and ideal preblurring (middle solid line). The optimization led to a value of \( w = 2.4 \) mm. 

![Fig. 3. Adjacent pixel responses in an unblurred system [31].](image)

![Fig. 4. Adjacent pixel responses in a blurred system [31].](image)

![Fig. 5. Improved sensor design [33].](image)

![Fig. 5. Improved sensor design [33].](image)
The optimal response corresponds to a blur radius (measured at the half-power point by convention) of 1 mm. Therefore, at the peak response, the blurred light lies exactly on top of the fiber. This means that preblurring does not necessarily decrease the peak response of a pixel to light. It has a negligible effect when applied correctly.

The second task in hyperacuity maximization is adjusting the amount of overlap between adjacent pixel responses. This was achieved by adjusting the inter-lens angle \( \Delta \phi \). We chose \( \Delta \phi \) such that the term in (3) was maximized. Fig. 7 shows the smoothed photodetector motion response as a function of the percentage of overlap, where

\[
\%\text{overlap} = 100 \times \frac{h(X_a)}{h(0)}.
\]

An overlap of approximately 50% yields the greatest motion acuity. The inter-lens angle, \( \Delta \phi \), was therefore chosen such that neighboring pixels had a 50% overlap over a wide range of distances. The ideal inter-lens angle approaches 7.8° as the object distance approaches infinity. However, in order to increase motion sensitivity at closer object distances, we chose value of \( \Delta \phi = 7.5^\circ \). Using this value for the inter-lens angle maximizes motion detection with an object distance of roughly 1.4 meters. In practice, this choice will depend on the application, but \( \Delta \phi = 7.5^\circ \) provides significant sensitivity to motion at all distances.

In order to evaluate and compare performance of the new sensor, an optical model of Benson’s earlier sensor was developed. Fig. 8 shows a comparison between the optical models of the new sensor (solid line) and Benson’s sensor (dashed line). The peak pixel response and motion acuity of the new sensor have improved by a factor of 4.

V. HARDWARE IMPLEMENTATION

We designed the sensor with the dimensions detailed in the previous section. The first prototype has seven pixels (lens/fiber pairs) in a nonplanar hexagonal configuration (depicted in Fig. 9). The field-of-view can easily be expanded by adding more lenses.

The terminal end of each fiber is connected to an IFD93 photodarlington (shown as the top device in Fig. 10). The IFD93 was chosen for its high sensitivity and simple interface design. Current proportional to the amount of sensed light \( I_s \) is generated by this photodarlington. A second IFD93 (shown as the bottom device in Fig. 10) generates current proportional to the amount of unfocused ambient light \( I_a \). This configuration prevents saturation and allows the sensor to be used in a wide range of lighting conditions. The ambient light detectors were connected to polished optical fibers (arranged hexagonally) without lenses. The ambient light detectors do not mimic the Musca domestica, which relies on chemical signaling [35] and adjusting its photoreceptor membrane size [36] to adapt to varying light conditions. The sensor signal is given by

\[
V_{\text{sensor}} = (I_s - I_a) \times R.
\]

The sensor is shown in Fig. 11 along with the designs by Riley and Benson. A penny is pictured for scale. The optical front-end of the new design is smaller than 1/4 the size of each of the other two.
After the sensor was constructed, a test setup was designed to compare the sensor’s output to the software model and to previous fly eye sensors. The test setup, depicted in Fig. 12, consisted of a stationary sensor placed a distance \( z = 1.0 \) m from a painted wood dowel on a conveyor belt. White felt was hung behind the conveyor belt. Numerous dowels were used to provide stimuli of varying size and contrast. Each dowel rod was either painted white (for low contrast) or black (for high contrast) and had diameter \( D \). The dowels were tall enough to span the vertical FOV of the sensor. The conveyor belt swept the dowel across the sensor’s horizontal FOV at a constant velocity of 0.62 m/s. The test setup was housed in a light-insulated room in order to provide consistent lighting conditions during each test. The experiment was illuminated by overhead fluorescent lights. The data was collected using a DATAQ DI-148U data acquisition system. WinDAQ/XL software was used to record the data with a sample frequency of 240 Hz.

Fig. 13 compares the normalized output from the sensor (shown as solid red lines) with the predicted output from the software model (shown in dashed black lines). The shapes of the sensor signals are approximately Gaussian and are similar to the software model prediction. Any oddities and asymmetries can be attributed to flaws in sensor construction (most likely related to fiber polishing and alignment).

We compared the new sensor to two earlier designs created by Riley and Benson. We tested each sensor’s signal-to-noise ratio (SNR) with a high contrast stimulus. Table I shows the calculated SNR for each sensor. The new sensor has a SNR of 2.78 times Benson’s sensor’s SNR. This is not as large of an improvement as the fourfold improvement predicted by the software model. However, the amount of gathered light (which the software model calculated) is not the only determining factor for the SNR. Noise is inherent in the sensor output due to a variety of sources, including the photodetectors and the amplification circuitry. It is likely that this noise, not considered in the software model, is the reason the new sensor produced slightly less improvement than first predicted. No specific noise mitigation techniques have yet been applied.

The new sensor clearly outperforms Riley’s sensor. This is interesting because of the similarity of the designs. This reinforces the idea that, when using a multiaperture design, a much stronger signal can be achieved without sacrificing the desired Gaussian shape or overlap.

Fig. 14 shows each sensor’s normalized response (from a single photoreceptor) to the same high contrast stimulus (a black bar with diameter \( D = 3.2 \) cm). Note the effect of the SNR on the overall response shape. Riley’s sensor’s signal (dot-dashed...
line) is considerably noisier than the other two, while the new sensor clearly generates the smoothest signal (solid line).

VI. CONCLUSION

We have designed a prototype of a sensor based on the visual system of the Musca domestica. The multiaperture sensor showed a significant increase in SNR and motion acuity over the previous fly eye sensors. The SNR for each sensor was proportional to the angular width of the bar (i.e., larger objects yielded a stronger signal, as expected). Furthermore, the SNR for the high contrast stimulus was appropriately proportional to the SNR of the low contrast stimulus. The increase in SNR results in a higher motion acuity, since the ability to detect motion in this sensor is limited only by the noise floor and the resolution of the analog-to-digital converter.

This prototype is simply the optical front-end of a complete fly eye sensor system. Analog circuitry (which mimics the Musca domestica’s L1, L2, and L4 neurons in the lamina) is being developed to extract edge and motion information with little to no processing (i.e., minimal CPU overhead). While they will never replace traditional imaging devices, multiaperture sensors show great promise to augment these devices by efficiently providing detailed edge and motion information in real-time.

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REFERENCES


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