Autonomous Mobile Robot Control Based on White Blood Cell Chemotaxis

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Abstract. This paper presents a biologically inspired algorithm to control an autonomous robot tracking a target. The algorithm is designed to mimic the behavior of a human neutrophil, a type of white blood cell that travels to sites of infection and digests bacterial antagonists. Neutrophils are known to be highly sensitive to low levels of chemical stimuli, robust to noise, and are capable navigating unknown terrain, all qualities that would be desired in an autonomous robot. In this paper we model a neutrophil as a collaborative control system, demonstrate the robustness of this algorithm, and suggest a computationally cheap method of implementation. Our simulations show that the performance of the robot is unaffected by constant disturbances and it is robust to random noise levels up to 5 times the tracking signal. Additionally, we demonstrate that this algorithm, as well the current models of neutrophil chemotaxis, are equivalent to a sensor fusion problem that optimizes directional sensing in the presence of noise.

1 Introduction

This paper presents a collaborative control algorithm based on the behavior of a neutrophil, a class of white blood cell. Created in the bone marrow, these cells passively travel through the blood stream, until they sense the chemical traces of an invading bacteria. At this point, they leave the blood stream, crawl through the endothelial cells to the site of infection and digest the intruder. Figure 1 shows a neutrophil about to digest a bacterium [11]. The ability of a neutrophil to move up a chemical gradient is referred to as *chemotaxis*. While this behavior is remarkable it is believed that the underlying mechanisms are simple, that is, there is not a high level algorithm or form of intelligence within the cell. It is more likely that there is a combination of simple controls [5][9]. Despite this assumed simplicity, it is believed that through the evolutionary process these cells have been optimized for their task [9]. This optimal design is what we attempt to reproduce here. The main contributions of this paper are 1.) we extend the work of Goldberg and Chen [2] by deriving a relationship for the performance/robustness tradeoff that was hinted at in their analysis

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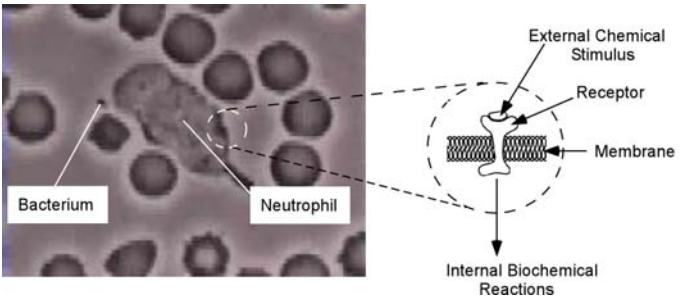

Fig. 1. A Neutrophil tracking a bacterium [11], and a schematic diagram of a transmembrane receptor

of collaborative control systems 2.) we show that current neutrophil sensing models are a special case of an optimal sensor fusion problem 3.) we suggest a computationally fast method for implementing this algorithm. Before going into our analysis and simulations, we review some of the observed behavior in neutrophils and collaborative control and elucidate how the two relate.

1.1 Neutrophil Review

This section presents a simplified view of the neutrophil sensory and actuation system. Trans-membrane receptors are evenly distributed around the periphery of the cell: their function is to transmit information from the environment to within the cell [8]. When a receptor binds to a signalling chemical it will initiate a series of chemical reactions that instruct the cell to move in the direction of the activated receptor. Figure 1 shows a schematic diagram of a transmembrane receptor with a bound chemical stimulus. Since there are many receptors (around 10,000) there is a competition as to which direction to move. This competition results in a net motion towards the target since the receptors reading the strongest signal (hence closer to the target) will "pull" harder than receptors reading a weaker signal. This sort of sensing scheme can be thought of as a vector sum: the true signal is proportional to the sum of the sensed signal at each receptor times its normal vector.

We hypothesize that this vector sum approach to signal evaluation makes the cell robust to noise. For example, if the chemical concentration is constant than each receptor detects the same signal, and each pulls with same force; therefore the cell will have no net motion. This is consistent with what is observed in the cell– it will only respond to a chemical gradient [13] [14]. Therefore a cell can adapt to any constant level of chemical stimulus and similarly, it is able to reject any constant noise or bias in its environment or sensing pathways. In the case of non-deterministic noise, there will not be perfect noise rejection, but one would expect some filtering or partial noise subtraction. This point was explored with our model.

In addition to noise-robustness, neutrophils have been observed to be very sensitive to changes in chemical stimulus. In fact, it has been shown that they respond to chemical gradients as low as a 2% difference across their length [3]

[14]. This has led many investigators to conclude that there must be some internal amplification within the cell. One hypothesis in that there is receptor coactivation, which means that when one receptor becomes active it sequesters important signalling chemicals towards its neighbors, thus making them more sensitive. The net effect of receptor coactivation is to make the up-gradient receptors more sensitive then the down-gradient receptors, which some authors refer to as "frontness" and "backness", respectively.

1.2 Collaborative Control Review

In collaborative control systems *multiple* sources share control of a single robot [2]. A source is an element that relates information about the environment and current state of the robot with the robot's objective and produces a control output. Sources can take many forms. The robot can be controlled by multiple sensors (*sensor fusion*), control processes (*subsumption*) or human operators. Essentially, collaborative control is an average control based on many sources trying to accomplish the same task. In fact, this is where we see the principle advantage: in a noisy environment the average control will be better than a single control. This advantage arises from the Central Limit Theorem and good engineering sense: multiple measurements will give you a better approximation of the "true signal" [2].

1.3 The Connection

We assume that the cell's ability to detect the direction of a chemical gradient arises from the collaboration of its receptors. Each receptor measures the signal and tries to move the cell in its normal direction. The sum of these controls results in the motion of the cell. As discussed above this "vector sum" methodology will be immune to constant noise. Furthermore, in our simulations we show that while it cannot completely reject random noise, it is able to track and pursue a target in the presence of high noise to signal ratios. We also demonstrate the advantages of source coactivation, which we formulate as an optimal direction sensing problem.

2 Related Work

The study of neutrophil chemotaxis is an active field, yet much about this system remains unknown. Current work focuses on understanding the chemical reactions that relate external stimulus to motion. This is important in understanding and preventing cancer metastasis as well as for engineering drugs that will cause an optimal immune response. The fundamental work on chemotaxis was done by Sally Zigmond in the 1970's [13] and an excellent review of recent work can be found in [14]. Current models of receptor coactivation and its relationship to signal amplification can be found in [3] [4]. The connection between neutrophil chemotaxis and cancer is discussed in [8] and good introductory papers on using engineering approaches in biology are [5] [9].

Much of the inspiration for this work came from Goldberg and Chen's analysis of collaborative control systems [2]. This paper is an excellent introduction to the field and formalizes a measure of robustness due to failing sources. Gerkey [1] attempted to refute the results of Goldberg and Chen, but their results were inconclusive. After careful examination of both papers, it is apparent that their disagreement stems from a misunderstanding of Goldberg and Chen's performance metric. Specifically, Goldberg's metric did not take into account the speed of the robot, where the robot in [1] traveled at a constant velocity.

3 Results

This section analyzes the robustness and performance properties of collaborative control systems. We first consider a system similar to that of Goldberg and Chen [2] and extend their work by formulating the robustness property that was hinted at in their paper. Next we derive a robustness/performance relationship for a collaborative control system by recasting the problem as a constrained optimization. Finally we show that our formulation of the collaborative control problem can be related to current neutrophil models. This relationship is important for two reasons: our robustness/performance analysis applies to neutrophils (this has not been shown in the literature) and second, the neutrophil models provide us with a computationally cheaper algorithm then our optimization.

3.1 Noise Robustness in Distributed Sensing Systems

Derivation. Figure 2 shows a schematic diagram of our proposed system. A robot of unit diameter has N sources distributed around its periphery (dark circles in the figure). Each source senses the local concentration of the surrounding chemical field. The outputs of the individual sensors are then combined (eg, averaged) and sent to the robot's actuators.

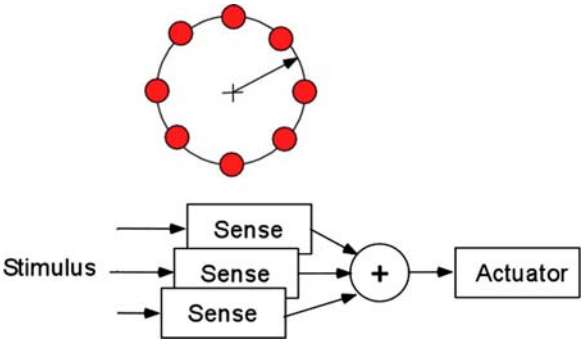

Fig. 2. Schematic diagram of simulation: A circular robot combines the input from its N sensor into a single signal that is then sent an actuator

We start by defining the output of each individual sensor, s_i:

$$s_i = (g_i + \nu_i)\overrightarrow{n_i} \tag{1}$$

$$\nu_i \sim \mathbb{N}(m, \sigma) \tag{2}$$

where g_i is the chemoattractant concentration, ν_i is sensor noise, $\overrightarrow{n_i}$ is the outward pointing normal vector at the i^{th}sensor. We assume that the noise on each sensor, ν_i is an independent normally distributed random variable with mean m and variance σ (equation 2). Our problem to combine the sensors readings so that that our robot moves in the correct direction. A simple and obvious scheme is to add the sensor readings; the resulting vector, $\overrightarrow{s}$, gives the direction and magnitude of the sensed signal. That is:

$$\overrightarrow{s} = \sum_{i=1}^{N}(g_i + \nu_i)\overrightarrow{n_i} \tag{3}$$

$$= \sum_{i=1}^{N} g_i\overrightarrow{n_i} + \sum_{i=1}^{\frac{N}{2}} \xi_i\overrightarrow{n_i} \tag{4}$$

$$\xi_i \sim \mathbb{N}(0, 2\sigma) \tag{5}$$

For large N equations 4 and 5 become:

$$\lim_{N\to\infty} \overrightarrow{s} = \nabla g + \mu \tag{6}$$

$$\mu \sim \mathbb{N}\left(\begin{bmatrix}0\\0\end{bmatrix}, \pi\sigma \mathrm{I}_2\right) \tag{7}$$

where I_2 is the two dimensional identity matrix. Equations 6 and 7 show that for many sensors, $\overrightarrow{s}$ approximates the gradient of the external field plus a zero mean gaussian noise process. This is significant because it shows that the vector sum of the sensors will cancel out any constant disturbances. In this sense, our collaborative control strategy acts as a high-pass filter. We now show the effectiveness of this control strategy with simulations.

Simulation. Our simulation consists of a circular robot with unit radius moving in a linear chemical gradient. The task of the robot is to move 10 units up-gradient (the positive y-direction) of its starting point, and its performance P is measured by the ratio of the minimum path length, L_{min}, to its total path length, L. That is,

$$P = \frac{L_{min}}{L} \tag{8}$$

The signal the robots senses is described by equation 3, where g linearly increases in the y-direction with unity slope. At each time step, the robot calculates $\overrightarrow{s}$ and then moves in that direction 1 unit. Clearly, any deviation from a straight path will decrease the value of P. Figure 3 shows the performance of the algorithm described by equation 3 for various levels sensor noise. The noise added to each

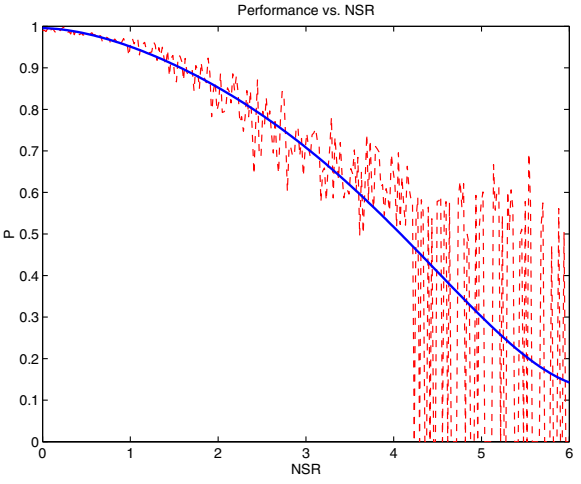

Fig. 3. Performance degradation as a function of random noise-to-signal ratio (NSR) for the algorithm described in equation 3. The red dashed line is taken from 300 experiments and the solid blue line a polynomial fit to the data

sensor is $\nu_i \sim \mathbb{N}\left(0, NSR^2\right)$. Remarkably, the robot is able to reliably accomplish its task (although with diminishing performance)until the $NSR \approx 4$. At this point, the robot is no longer able to distinguish between sensor noise and the true signal and therefore its motion appears brownian.

3.2 Improving Performance

While the algorithm presented above proved to be robust, it is also very conservative– it equally weights the signal from each sensor even though some will have a better NSR then others. In particular, the up-gradient sensors will have have a lower NSR then the down-gradient sensors and therefore they should contribute more to the estimated signal. So instead of taking a vector-sum of the sensor readings, we propose taking a weighted average, where the weighting will be a function of the NSR.

Derivation. We begin by defining our signal s and weighting vector $w \in \mathbb{R}^N$

$$s = w^T(g + \nu) \tag{9}$$

$$\sum_{i=1}^{N} w_i = 1 \tag{10}$$

where $g, \nu \in \mathbb{R}^N$ are the detected signal and noise vectors, respectively. (We have dropped the vector notation for s and will now assume that we are in polar coordinates with the origin at the cell's center.) Our new problem is to choose w

such that we maximize the detected signal in the correct direction. We formulate this optimization as

$$\hat{w} = \arg\max_{w} \left(\mathbf{E}\left[s\right]^2 - var(s)\right) \tag{11}$$

The first term on the right in equation 11 causes w to be high near sensors receiving a high signal, and the second term penalizes the objective function when the variance in the noise is high. Therefore, if there is high uncertainty in the sensor reading then second term in equation 11 prevents the weighting of noisy sensors.

After some manipulation, equation 11 can be put in the following quadratic form:

$$\hat{w} = \arg\max_{w} \left(w^T A w\right) \tag{12}$$

$$A = gg^T - \sigma \mathrm{I_N} \tag{13}$$

$$\sigma = NSR^2 \tag{14}$$

This can be solved analytically with the Lagrange Dual Function.

$$\hat{w} = A^{-1}\lambda e \tag{15}$$

$$\lambda = \frac{1}{e^T R^{-1} e} \tag{16}$$

where $e \in \mathbb{R}^N$ is a vector of ones. However this formulation allows for negative values of w_i because A is sign indefinite. This is not useful for our application so we solve equation 12 numerically with the added constraint $w_i \geq 0$.

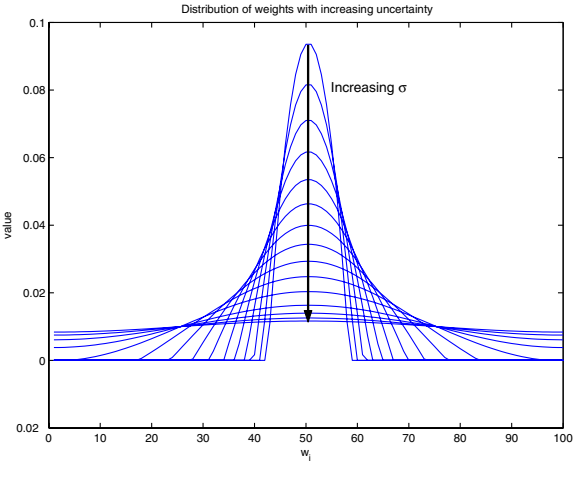

Fig. 4. Polarity vector w as noise variance, σ, increased from $1 \rightarrow 300$

Simulation Figure 4 shows how the weighting vector w changes with increasing noise level, $\sigma = 1 \rightarrow 300$ (the values are evenly spaced on a log scale), and g is a linear gradient with unity slope. For small σ, w heavily weights the sensors near the highest value of g and as σ increases, w weights the sensors evenly.

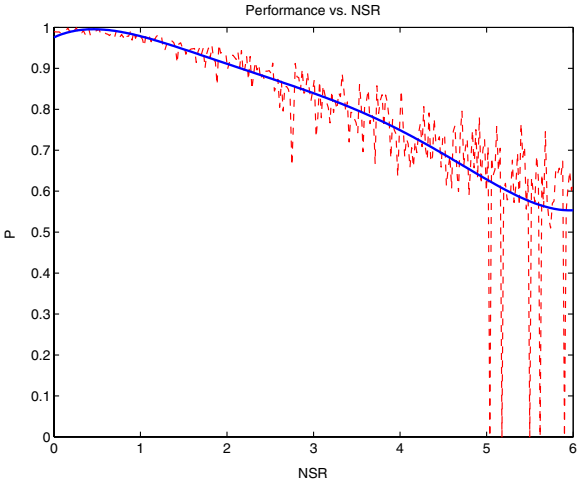

Fig. 5. Performance degradation as function of random noise-to-signal ratio (NSR) for the algorithm described in equations 10 and 12. The red dashed line is taken from 300 experiments and the solid blue line a polynomial fit to the data

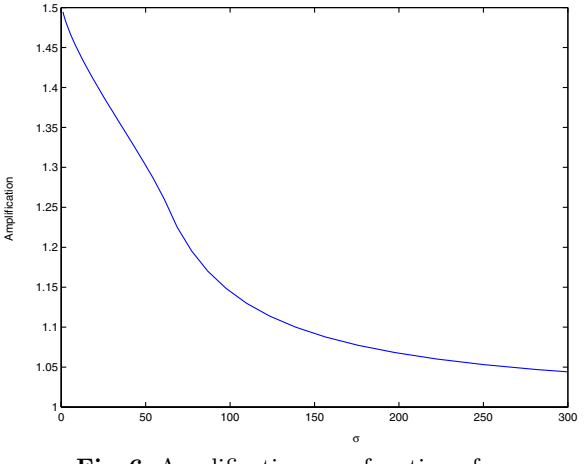

Fig. 6. Amplification as a function of σ

We tested this new algorithm using the same simulation strategy as in section 3.1, except that at each time step w is recalculated. Figure 5 shows the

performance of this algorithm with increasing NSR. In this case w was calculated assuming $\sigma = 16$ so that the algorithm would be robust to $NSR = 4$. Comparing figures 3 and 5 shows that our new algorithm improved performance for $NSR = 1 \rightarrow 4$ and that it did not fail until after $NSR \approx 5$. When we optimized for $NSR \geq 10$, which results in a "flat" w, the performance of the system was similar to 3, and when we optimized for $NSR < 10$ all of our results looked very similar to figure 5.

In addition to improving noise robustness, the asymmetric weighting of the sensors amplifies the detected signal. We define amplification as the ratio of s from equation 10 to the slope of the gradient (in this case the slope is one). Figure 6 quantifies the signal amplification for different w vectors, where w is parameterized by the noise variance σ. As would be expected from equation 10, a highly asymmetric w will give a higher amplification since up-gradient sensors make a larger contribution to s, and as $\sigma \rightarrow \infty$ the amplification will go to one. Our performance simulations did not include the effect of the amplification since the speed of the cell was held constant. This was done so that we could directly assess the effect of w on direction sensing and not on the speed of the robot. However, we include the results of figure 6 to demonstrate that the signal amplification discussed in [13] and [14] could come from the weighted collaboration of the cell's sensors.

3.3 Connection to Neutrophil Models

In the formulation above we showed that the preferential weighting of sensors leads to increased performance and noise robustness of a gradient sensing robot. The models of [3], [10], and [7] describe the dynamics and asymmetric distribution of PH (Pleckstrin Homology) proteins in chemotaxing Eukaryotes (specifically neutrophils and *Dictyostelium discoideum*). The PH proteins accumulate at the front or up-gradient region of the cell membrane and it is thought that this makes the front more sensitive to chemical stimuli then the back. Their models differ in how this asymmetry of proteins evolve and how the dynamics relate to the known biochemistry. However, their models are similar in that when presented with a temporarily stable gradient the distribution of PH proteins is similar to our calculated w vector (with slight modification to their parameters we can make them equivalent). Therefore the performance and robustness results of our algorithm can be directly applied to their models. In this sense, their models are a special case of our optimal sensing formulation.

Additionally, this similarity leads to a novel way of implementing our algorithm on an autonomous robot. Instead of computing the optimal w vector at each time point, we can design a circuit for each sensor that mimics these neutrophil models. For example, each sensor could be given the following dynamics:

$$\frac{da_i}{dt} = g_i - k_a a \tag{17}$$

$$\frac{db_i}{dt} = k_s g_i - k_b b \tag{18}$$

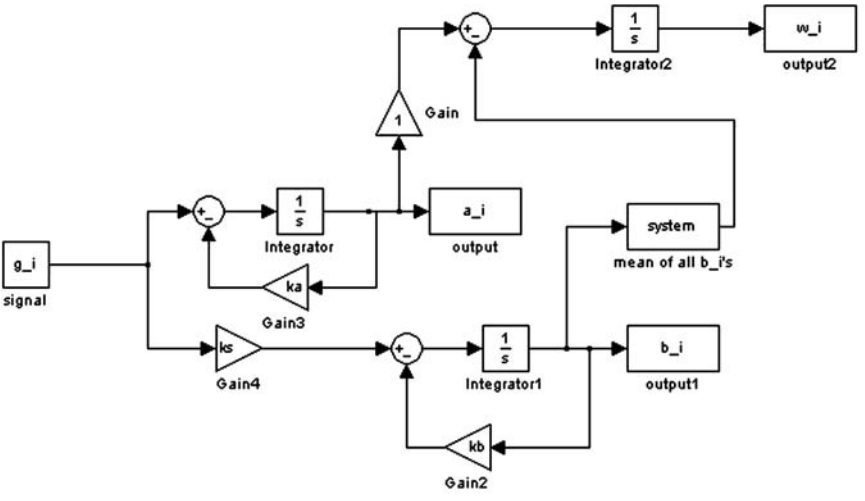

Fig. 7. Schematic diagram of proposed circuit for computing w_i

$$\frac{dw_i}{dt} = a_i - \frac{1}{N}\sum_{i=1}^{N} b_i - k_w w_i \tag{19}$$

Equation 19 describes how the the weight, w_i, on each sensor changes as a function of a and b. We refer to a as the "activator" dynamics– a_i increases with increasing g_i which in turn increases w_i. We refer to b as the "global inhibitor"– it subtracts off the mean value of the received signal for all w_i. The interplay of the activator and global inhibitor leads to an asymmetric distribution of w_i's. The constants, k_x, are design variables that will affect the dynamics and distribution of w. This method of sensor weighting can be implemented in hardware with 7 op-amps (3 integrators and 4 gains) per sensor and one summing circuit (for computing the mean). Figure 7 shows the configuration of this circuit. Clearly this will be a much faster method of computing w then by solving the quadratic optimization problem.

4 Conclusions and Future Work

This paper has presented and analyzed a biologically inspired algorithm for collaborative control. We have evaluated the algorithm's performance and noise robustness and have suggested how to implement the algorithm with hardware. We have also shown how current neutrophil models are similar to our formulation, which suggests that neutrophils are robust to noise in their signaling pathway. Our next task will be to evaluate how the dynamics of w and the resulting amplification effect the performance of a robot in an obstacle field. Preliminary results show that if w has fast dynamics (that is, can quickly redistribute) the robot is better at avoiding obstacles but it is more sensitive to noise.

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