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A robotics approach for interpreting the gaze-related modulation of the activity of premotor neurons during reaching

Christophe Halgand, Philippe Souères, Yves Trotter, Simona Celebrini, and Christophe Jouffrais

Abstract—This paper deals with the modeling of the activity of premotor neurons associated with the execution of a visually guided reaching movement in primates. We address this question from a robotics point of view, by considering a simplified kinematic model of the head, eye and arm joints. By using the formalism of visual servoing, we show that the hand controller depends on the direction of the head and the eye, as soon as the hand-target difference vector is expressed in eye-centered coordinates. Based on this result, we propose a new interpretation of previous electrophysiological recordings in monkey, showing the existence of a gaze-related modulation of the activity of premotor neurons during reaching. This approach sheds a new light on this phenomenon which, so far, is not clearly understood.

I. INTRODUCTION

To plan and control a reaching movement toward a visual target, the Central Nervous System (CNS) of primates needs to perform various transformations to match sensory and motor variables encoded in different coordinates. Different experiments tend to prove that the reference input used by the CNS for planning the motion is the position error – called “difference vector” – between the hand and the target [1]. In order to make the encoding of this difference vector possible, the hand and the target need to be expressed in the same reference frame. The question of which spatial reference is used by the CNS to encode this vector has been debated since a long-time in neurosciences.

A first way of thinking was that the CNS encodes the difference vector with respect to the body. This idea was suggested by early experiments showing that, during motion, the activity of different cortical areas varies as a function of the end-effector location with respect to the body [2], [3], [4].

Physiological evidence has progressively convinced neuroscientists that the CNS rather encodes the hand-target difference vector in visual coordinates. Cohen and

Andersen [5] suggested the existence of a common eye-centered reference frame for movements plans. It was shown that this eye-centered spatial representation constitutes a reference for multisensory integration, illustrating the predominant role of vision in primates [6]. Buneo et al. [7] observed that, when the relative hand-target position remains constant with respect to the fixation point, the activity of dorsal area 5 cells varied little, suggesting that the difference vector is encoded in fixation-centered coordinates. Finally, numerous psychophysics studies have strengthened the idea that visually guided movements are planned in an eye-centered frame [8].

However, though an increasing number of neuroscientists agree that the CNS encodes the hand-target difference vector in a visual frame, most models of reaching control still consider the body as the basis of the movement, without considering the influence of the eye and head position. For instance, most research studies, which aim at determining the cost criterion that is minimized by the CNS during reaching, simply consider that the target position, with respect to the body, is known [9]. Many models dealing with coordinates transformations emphasize the central role of vision for the integration of motor plans, but consider at the end that movement is organized from the trunk [6] [10]. A striking illustration of this fact is given by the computational model of control proposed by Shadmehr and Wise in their famous book devoted to the neurobiology of reaching and pointing [1]. This model, represented in Fig. 1, is based on the hypothesis that the difference vector is expressed in a fixation-centered frame but only consider the kinematic transformations associated with arm joints. The authors argue that, when the eye or the head position are modified, both the hand and the target positions are shifted by a same amount in retinotopic coordinates and, as a consequence, the representation of the difference vector remains identical with respect to the eye frame. This reasoning is questionable because, though vector coordinates are actually invariant under translation they should be modified by rotations induced by eye and head angles.

On the other hand, electrophysiological studies in monkey have shown that, during visually guided reaching movement with an imposed fixation point, the activity of premotor neurons is qualitatively and quantitatively modulated by gaze direction [11], [12] [13], [14]. These interesting results reveal that the eye and head positions are actually involved in the computation of the

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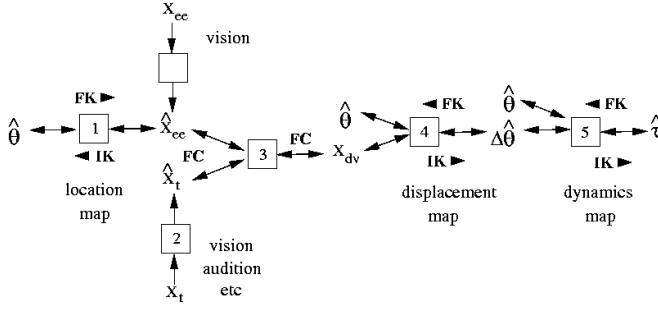


Fig. 1. From Shadmehr and Wise [1]-p246 : Virtual robotics model describing the successive transformations involved in a reaching task. First, the position of the target, \hat{x}_t , and the position of the end-effector, \hat{x}_{ee} , are both transformed in fixation-centered coordinates (networks 1 and 2). Then, the difference vector x_{dv} is computed as the gap between \hat{x}_t and \hat{x}_{ee} (network 3). Taking the difference vector x_{dv} and the current arm configuration $\hat{\theta}$ as input, the internal model of inverse kinematics allows to determine an infinitesimal variation of arm joints, $\Delta\hat{\theta}$, that allow to drive the hand toward the target along x_{dv} . Finally, from $\Delta\hat{\theta}$ and $\hat{\theta}$ the internal model of inverse dynamics allows to compute the necessary torque $\hat{\tau}$ to execute the movement. Note that the terms $\hat{\theta}$ or $\Delta\hat{\theta}$ are related to arm joints only, and that the eye and head angles are not considered in this model. FK and IK respectively stand for forward kinematics and inverse kinematics, whereas FC is used to specify that data are expressed in fixation centered coordinates.

arm controller. This effect was however considered as a marginal one by the neuroscientists who share the belief that motor control is organized from the body. For instance, Shadmehr and Wise interpreted the gaze influence on premotor neurons as the neural expression of the well-known fact that movement accuracy in primates depends on the angle between the target and the fixation point [1].

The goal of this paper is to shed a new light on this question by considering it from the point of view of robotics. We propose to study the transformations inherent in the computation of a vision-based reaching controller, by using a simplified kinematic model of the head, eye and arm joints involved in the task. We use the formalism of visual servoing to design a controller that allows to drive the hand to the target while controlling the gaze direction. By this, we want to show that the eye and head angles are intrinsic parameters of the hand controller, as soon as the hand-target difference vector is expressed in visual coordinates. After giving the analytic expression of the controller we will implement it as a feedforward artificial neural network, similar to the ones proposed by several authors dealing with coordinate transformations [10]. This neural network will be trained to execute reaching movement with prescribed gaze direction. The activity of single artificial neurons will be analyzed and compared with the results reported in [15]. Based on this study, a new interpretation of the gaze-related modulation of premotor dorsal (PMd) neurons during reaching will be proposed.

II. PREVIOUS ELECTROPHYSIOLOGICAL RESULT

This section briefly recalls the experimental result by Jouffrais et al. [15], which reveals the existence of a qualitative and quantitative gaze-related modulation of the activity of premotor neurons during visually guided reaching in monkey.

Behavioral task

Two macaque monkeys were trained on a visually guided reaching task. To begin a trial, the monkey had to put its hand on a target at the center of a screen. When the fixation spot appeared, the animal was required to orient gaze and maintain fixation during the upcoming period of the trials. Then a white target appeared which turned grey after a delay. The monkey had to move its hand to this target without moving gaze (Fig. 2 A). In the experimental paradigm, the fixation spot was presented at nine different positions. This design required the monkey to make limb movements in a given direction, while gazing at various locations (Fig. 2 B).

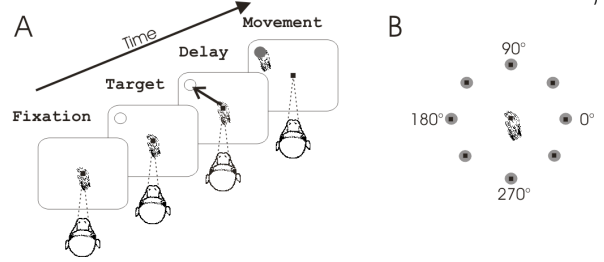


Fig. 2. Behavioral task : (A) illustrates the case where the monkey fixates the central point and reaches a peripheral targets. The nine fixation points and targets (B) were successively considered

Results

129 set-related PMd neurons showing a preferred direction (PD) (bootstrapping test, $p < 0.05$) and/or a gaze modulation (ANOVA, $p < 0.05$) were recorded. For most of these cells, the PD vector tended to shift with gaze. In many cases, the highest activity was associated with movements made towards the fixated target. In less than half of the trial, the PD remained stable, independent of gaze angle, but the magnitude of the PD changed. The following figures illustrate how the gaze position modulates the PD. 3/41 (7%) cells show a gain modulation of the PD due to gaze position (ANOVA, $p < 0.05$). 15/25 (60%) cells show a rotation of the PD due to gaze position (Watson-Williams test, $p < 0.05$).

Conclusion

This study, as well as the previous works [16], [11] and [12], demonstrate that directional coding of arm movement in PMd (and M1) is dependent of gaze direction. However the current biological models of PMd activity do not allow to clearly explain the reason of this dependency.

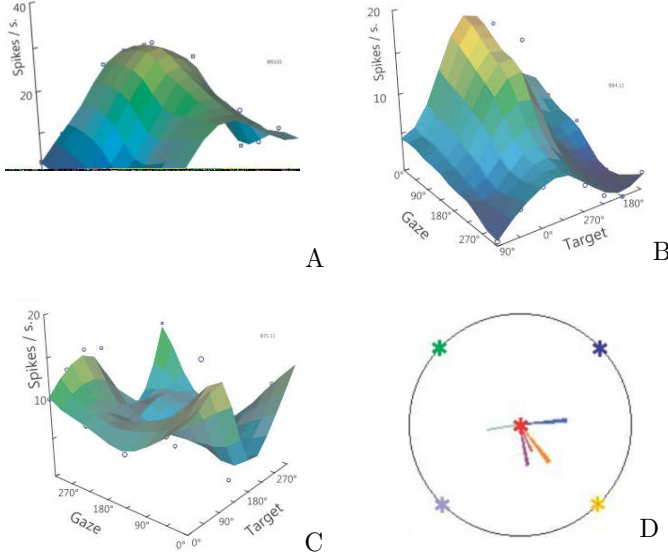


Fig. 3. Typical examples of PMd cells with reach-related activity : A : independent of gaze position, B : dependent on gaze position (preferred direction (PD) is not modified, but is gain-modulated by gaze position), C : dependent on gaze position (PD is modified by gaze position, indicated by *), D : shows how the PD of the neuron represented in C rotates with gaze position.

III. THE KINEMATICS OF VISUALLY GUIDED REACHING

In this section we explain how the formalism of robotics, and more specifically the visual servoing framework, can be used to design a vision-based kinematic controller to execute reaching movements. In the literature devoted to the neurobiology of reaching and pointing the « eye frame » is usually attached to the dominant eye [1]. We will use the same convention here by considering a model of « cyclopean » robot. We consider a simplified model of the human upper body in which the trunk is supposed to be fixed, as represented in Fig 4. This model includes 7 degrees of freedom (DoF) at the arm (3 at the shoulder, 2 at the elbow and 2 at the wrist), plus 2 DoF at the neck and 2 DoF at the eye.

In order to design the visually guided reaching controller, we use visual servoing. First we recall the basics of this approach by following the presentation proposed in [17]. Basically, visual servoing aims at controlling robot motion by regulating an output function e , called « task function », defined as the gap between the current value of a vector of k visual feature $s \in \mathbb{R}^k$ and the desired one s^* :

$$e = s - s^*$$

The interaction matrix L_s , associated with s , allows to express the differential link between the time derivative of the task function and the velocity of the camera v_c :

$$\dot{e} = L_s v_c$$

In visual servoing, 2D and 3D features can be considered. However, to simplify our presentation, we will consider here that the visual features are simply 2D projection

of points $s = (X, Y)^T$ in the camera image plane, and that L_s is the interaction matrix associated to a point.

Two situations are to be considered. Either the camera is attached to the end-effector of the robot, defining an « eye-in-hand » system, or it is placed aside the robot and constitutes a « eye-to-hand » system. In both cases, the system equations in joint space have the same form :

$$\dot{e} = J_e \dot{q} + \frac{\partial e}{\partial t} \quad (1)$$

where, $q \in \mathbb{R}^n$ is the joint vector of the robot, $J_e \in \mathbb{R}$ is the feature Jacobian matrix and $\partial e / \partial t$ expresses the variation of visual features which is independent of joint variations.

- For an eye-in-hand system, J_e is expressed by :

$$J_e = L_s {}^c V_n {}^n J(q)$$

where ${}^c V_n$ is the transformation matrix from the camera frame R_c to the end-effector frame R_n (n^{th} link). If the camera is rigidly fixed to the end-effector, ${}^c V_n$ is constant. ${}^n J(q)$ is the robot Jacobian expressed in R_n . In this case, $\partial e / \partial t$ represents the time-variation of s due to potential object motion.

- For a eye-to-hand system, J_e is expressed by :

$$\begin{aligned} J_e &= -L_s {}^c V_n {}^n J(q) \\ &= -L_s {}^c V_b {}^b J(q) \end{aligned} \quad (2)$$

where, in the first line of (2), the robot Jacobian ${}^n J(q)$ is expressed in R_n and the transformation ${}^c V_n$, from R_c to R_n changes all along the servo ; whereas, in the second line of (2), ${}^b J(q)$ is expressed in the robot frame R_b (base) and the transformation ${}^c V_b$ from R_c to R_b is constant, as long as the camera does not move. In this case $\partial e / \partial t$ represents the time-variation of s due to the potential camera motion.

In both cases, a kinematic controller can be obtained by inverting equation (1), using for instance the Moore-Penrose pseudo-inverse $J_e^+ = J_e^T (J_e J_e^T)^{-1}$. The following expression of the controller is then obtained :

$$\dot{q} = J_e^+ (\dot{e} - \frac{\partial e}{\partial t}) \quad (3)$$

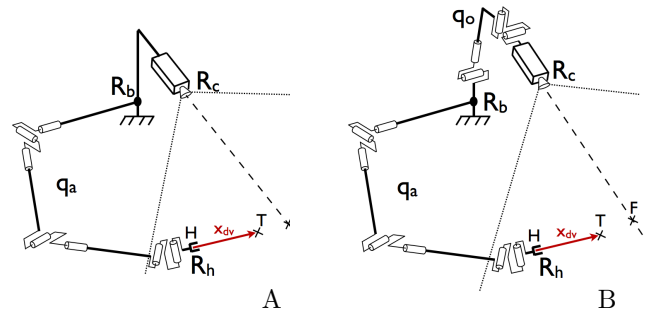


Fig. 4. Simplified kinematic model of eye, head and arm joints involved in the visually guided reaching task

In view of this formalism, let us go back to our problem of designing a vision-based reaching controller. In order to

clearly describe our reasoning, we will proceed in two steps. Suppose first, as in Fig 4-A, that only the arm joint may vary, while the body frame R_b (trunk) and the camera frame R_c are fixed. This configuration constitutes an eye-to-hand system. The visual servoing task we consider is to drive the reference point of the hand H to reach the target position T . The task function is then defined by the difference vector x_{dv} expressed in the eye frame :

$$e = x_{dv} = s_H - s_T \quad (4)$$

According to (1), as $R - c$ and T are fixed, $\partial e / \partial t = 0$. Denoting by q_a the vector of arm joints, we get :

$$\dot{e} = J_e \dot{q}_a$$

where $J_e = -L_{s_H} {}^cV_b {}^bJ(q_a)$. In this expression, cV_b describes the transformation between the camera frame R_c and the body frame R_b , which, in situation A, is constant, and ${}^bJ(q_a)$ is the Jacobian associated with the joints q_a , expressed in R_b . From (3), the controller expresses :

$$\dot{q}_a = J_e^+ \dot{e}$$

Clearly, this first representation is not sufficient for our purpose as we also need to control the gaze. To this end, consider now the configuration of Fig. 4-B in which the additional joints q_0 (neck and eye joints) have been introduced between the fixed body frame R_b and the camera frame R_c . In this configuration, two vision-based tasks are to be executed simultaneously : the fixation and the reaching.

- The first task e_1 is to drive the camera in order to place and maintain a new fixation point at the center of the camera image plane. If we denote by F the current position of this point and $F^* = 0$ the desired one, this task expresses :

$$e_1 = s_F - s_{F^*}$$

For this task, the joints q_0 linking the body to the camera constitute a eye-in-hand system. As the fixation point cannot move independently from the camera, $\partial e_1 / \partial t = 0$. According to (3) a gaze controller is given by :

$$\dot{q}_0 = J_{e_1}^+ \dot{e}_1 \quad (5)$$

where

$$J_{e_1} = L_{s_F} {}^cV_b {}^bJ(q_0) \quad (6)$$

- The second task $e_2 = s_H - s_T$ is to drive the hand to the target. This task is similar to the one introduced in (4) for the situation A, except that, here, the movement of the camera due to the execution of the task e_1 introduces a nonzero term $\partial e_2 / \partial t$ in the dynamics of e_2 . According to (3), the reaching controller expresses then :

$$\dot{q}_a = J_{e_2}^+ \left(\dot{e}_2 - \frac{\partial e_2}{\partial t} \right) \quad (7)$$

with

$$J_{e_2} = -L_{s_H} {}^cV_b {}^bJ(q_a) \quad (8)$$

and, according to (5) and (6),

$$\begin{aligned} \frac{\partial e_2}{\partial t} &= \frac{\partial e_2}{\partial q_0} \dot{q}_0 \\ &= (L_{s_H} - L_{s_T}) {}^cV_b {}^bJ(q_0) J_{e_1}^+ \dot{e}_1 \\ &= (L_{s_H} - L_{s_T}) {}^cV_b {}^bJ(q_0) [L_{s_F} {}^cV_b {}^bJ(q_0)]^+ \dot{e}_1 \end{aligned} \quad (9)$$

In order to complete the expression of this controller a decay rate needs to be defined for each of the two tasks e_1 and e_2 . For the fixation task e_1 we chose an exponential decay by setting $\dot{e}_1 = -\lambda e_1$ with $\lambda > 0$, as usually in visual servoing. However, for the second task e_2 , we applied the dynamics proposed by Hoff and Arbib in [18], in order to obtain the minimum-jerk dynamics observed in human. This is done by making e_2 obey the following third order dynamics :

$$\ddot{e}_2 = -\frac{9}{D} \dot{e}_2 - \frac{36}{D^2} e_2 - \frac{60}{D^3} e_2 \quad (10)$$

in which D is the movement duration.

Now, we have all the elements to conclude the first part of our reasoning. Indeed, we can observe that different terms in the expression of the reaching controller (7) depend on the joints q_0 that link R_c to R_b . This dependency occurs both in the terms cV_b and ${}^bJ(q_0)$, which appear in the expression of J_{e_2} (8) and $\partial e_2 / \partial t$ (9). Recall that cV_b represents the spatial transformation between R_c and R_b , which is a function of the joints q_0 continuously modified during the movement, whereas ${}^bJ(q_0)$ is the robot Jacobian associated with q_0 expressed in R_b .

This reasoning, shows that, as the reference of the movement is expressed in visual coordinates, the eye and head angles are intrinsic parameters of the hand controller.

IV. MODELING THE REACHING CONTROLLER WITH AN ARTIFICIAL NEURAL NETWORK

The kinematic analysis presented in the preceding section provides computational arguments for interpreting the activity of the CNS associated with the control of reaching movements. In primates, the premotor dorsal cortex (PMd) is known to be involved in the computation of motor plans and sensorimotor integration. By analogy with the robotics model, if the difference vector is expressed in eye-centered coordinates, one can expect that the activity of a large part of neurons involved in arm kinematics, i.e. premotor neurons, will be modulated by gaze position.

In the neuroscience community, many authors use artificial neural networks for representing models of multisensory and sensorimotor integration. These works consist in developing models of neural networks that allow to execute a given task, and then simulate and compare the activity of artificial units with the activity of real neurons. For instance, numerous authors proposed neural network models to reproduce coordinate transformation processes, from eye-centered frame to head-centered or

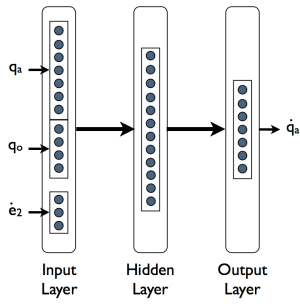


Fig. 5. Schematic representation of the artificial network

body-centered frames [19], [20], [10]. Using this approach they show that the eye and/or head position modulates the activity of artificial units, mainly in the hidden layer of the network. These results are consistent with electrophysiological recordings in the parietal posterior cortex, confirming the idea that this cortical area is involved in multisensory and visuomotor integration.

Following the same approach, we developed an artificial neural network to reproduce the function of the visually guided reaching controller described in section III. Our goal was to compare the activity of the artificial units located in the hidden layer of this network with the activity of real premotor neurons described in [15]. To this end, we simulated the reaching task by using the same kinematic conditions as in the behavioral task described in section II. The subject was standing in front of a screen, with the trunk and head fixed and aligned. While maintaining its gaze at a fixation point, he must execute a reaching movement to one of the eight targets placed in front of him

Network description

The artificial neural network was implemented in Matlab by using the Neural Network Toolbox and customized functions. We use the same architecture as in [21] [10]. The network is feedforward with one hidden layer, as described in Fig 5. In order to have a consistent decrease of the number of units in the successive layers, we put 12 units in the hidden layer. The activation function of these units is an hyperbolic tangent. We used the Levenberg-Marquardt backpropagation technique [22] to adjust the weights and biases during the training. As in [10], we stopped the training when the evolution of the root-mean-squared error (RMSE) was no longer perceptible on a log-log scale, the gradient became $< 10^{-6}$.

Training

In order to constitute a database for training the network, we simulated a large number of reaching movements by using the visual servoing controller designed in section III. By considering the 72 combinations (8 movements \times 9 fixation points), with 50 iterations for each movement, we recorded a set of angular configurations of the arm, q_a , and of the eye-neck chain, q_0 . To define the movement

direction we used a set of 3600 unit vectors uniformly distributed on a spherical surface, as in [10]. For the training, the network received as input : one unit vector indicating the direction of movement, a configuration of the arm and an eye position. The desired output was computed by applying the reaching controller (7) to the kinematic model of the mannequin.

Result

Fig. 6 represents the reaching trajectories to the eight targets that were obtained with the artificial neural network. We used different colors to represent trajectories corresponding to each of the nine fixation points. These trajectories are very close to the almost straight trajectory that was obtained with the controller (7) by applying the minimum-jerk criterion [18]. We found that the shape of trajectories is not correlated with the position of the target, nor with the fixation point or the eccentricity (ANOVA one way $p < 0.05$). This result shows that the artificial neural networks executes the reaching task with a good precision.

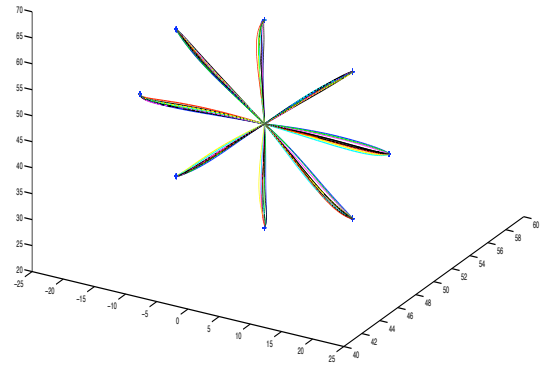


Fig. 6. Hand trajectories produced with the artificial neural network. Different colors correspond to the different fixation points

During the execution of these 72 reaching movements, we analyzed the mean level of activity of the 12 units of the hidden layer. This analysis shows that the activity of these units is modulated by the gaze direction and by the target position. More precisely, we found that the pattern of activity of these 12 units can be classified in three categories, as represented in Fig. 7

- 3 units had their level of activity mainly modulated by the eye direction as in Fig 7-A,
- 7 units had their level of activity mainly modulated by the target position as in Fig 7-B,
- 2 units had their activity modulated by both the eye direction and the target position as in Fig 7-C.

Though artificial neural networks are far from representing the actual activity of biological neurons, it is interesting to compare these patterns with the ones reproduced in section II. Our objective is to provide computational arguments to support the idea that premotor neurons are involved in the computation of the vision-based control

of the hand and, as a consequence, have their activity modulated by change in eye and head direction. Note that, beyond a simple modulation of the level of activity, we found that, for some units, the preferred direction was also modified. Indeed, certain units have a higher level of activity for a particular direction of reaching (as described in [4]), this direction sometimes varies as a function of the gaze direction. This observation is consistent with the result described in [15], in which the gaze modulation effect was not only quantitative but also qualitative.

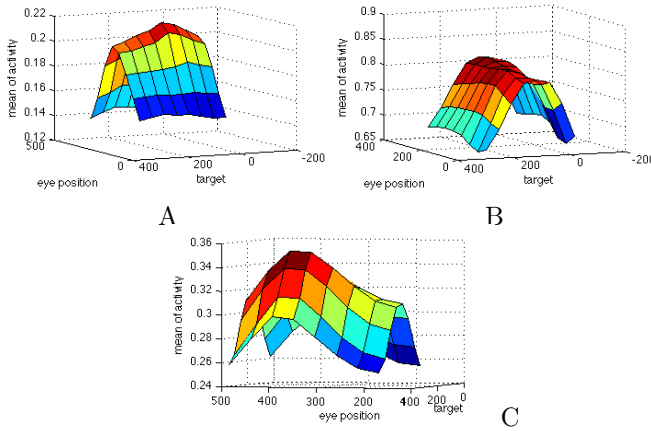


Fig. 7. Three characteristic patterns of activity of artificial neurons. A : mainly modulated by gaze direction, B : mainly modulated by target position, C : combined effect

V. CONCLUDING DISCUSSION

The current study leads to a more general discussion about the role of PMd in motor control of human and nonhuman primates.

Instead of considering that the role of PMd is to compute the difference vector and express it in body-centered coordinates, as proposed by [10], we suggest that the neurons of this area could be involved in the computation of the control at the kinematic level. According to this idea, premotor neurons could encode the differential link that allows to determine an instantaneous variation of joints to drive the hand in the direction of the difference vector, as already suggested in [1]. However, the important difference with Shadmehr's model is that here we suggest that, if the difference vector is expressed in visual coordinates, then the activity of neurons in this area must be modulated not only by the variation of arm joints, but also by changes in eye position in the orbit [11], [12], [13] and head position with respect to the trunk as predicted by Batista et al. [14]. The robotics approach and, in particular, the visual servoing formalism, provide a clear mathematical framework for modeling the transformations inherent in the computation of the reaching controller, and show this dependency.

VI. ACKNOWLEDGMENTS

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