Appendix S1. Off-line processing and cluster analysis of physiological (kinetic and kinematic) recordings

In accordance with the diagrammatic representation of the experimental design illustrated in Fig. S1A-E of this Supplemental Data, each global file (i.e., the complete set of kinetic and kinematic parameters; see Fig. 2 of the main text) was analyzed by applying an automated algorithm for physiological parameters estimation. Tables 1 and 2 describe the 60 physiological parameters measured: 24 kinetic (Table 1) and 36 kinematic (Table 2). Table 3 lists the 14 physiological parameters (4 kinetic and 10 kinematic) used for the analysis illustrated in Figure 3B of the main manuscript.

Parametric vectors of 60 components were obtained, one for each trial. The parameters of the different trials corresponding to the same block and session were averaged, component by component, for all the experimental subjects (n = 5 animals in this case). The resulting mean vector characterized an averaged block. The total number of averaged blocks was 15 x 12 = 180, i.e., 15 sessions and their respective 12 blocks. Hence, the parametric vector matrix could be represented as
The SS matrix comprised \( k \times j \) averaged blocks, each of which was of the form \( \bar{B}(N, i, p, tNip) \) and characterized the average of the \( tNip \) trials taken from the \( p \)th block of the \( i \)th session of all the experimental subjects. The value \( tmip \) refers to the number of trials taken from the \( p \)th block of the \( i \)th session of the \( m \)th subject.

A hierarchical clustering algorithm of averaged blocks was implemented on the basis of the combination of metrics ('Euclidean', 'seuclidean', 'Mahalanobis', 'cityblock', 'Minkowski', 'cosine', 'correlation', 'hamming', 'Jaccard') and methods ('single', 'complete', 'average', 'centroid', 'ward'), thus providing an exhaustive statistical characterization of the similarity among the \( \bar{B}(N, i, p, tNip) \) vectors and of the consistency of the clustering algorithm (Banfield and Raftery, 1993; Hair et al., 1998; Taganova and Silakov, 1980; Ma et al., 2006).

The main outcomes of the procedure were i) the optimal metric and the similarity matrix; ii) the optimal method and the single linkage matrix; iii) the optimal cophenetic correlation coefficient and the inconsistency matrix; and iv)
the cluster data report matrix which determined the clusters and their composition. The last-mentioned matrix could be represented in a hierarchical cluster tree, or dendrogram, like the one shown in Figure 3A of the main text.

We used a clustering variant that made it possible to distribute the contribution of each component according to a weight vector $0 \leq Wgts(c) \leq 1, \quad c = 1, \ldots, 60$, in which the values nearer to unity characterized more-significant components. The weight of the 14 parameters represented in Figure 3B of the main text was equal to unity for the specified value of the clustering statistical coefficient (0.97; the closer the value of the cophenetic correlation coefficient is to 1, the better the clustering solution). In Table S1 are indicated the characteristic values of the hierarchical clustering algorithm. According to data included in Table S1, the number of significant clusters was 15. It should be noticed that the 15 significant clusters included 83.89% of the averaged blocks, and that only 16.11% of the remaining averaged blocks fell into another 15 clusters, with the following distribution: 7 clusters with 1 averaged block, 3 clusters with 2, 1 cluster with 3, 2 clusters with 4, and 1 cluster with 5 averaged blocks (see Fig. 3A of the main text).

This algorithm for the post-processing of physiological records provided more homogeneity in the experimental database for the subsequent dynamic correlation analysis. The global files were clustered in an automated way, taking into account physiological criteria based on a characterization of the activity of orbicularis oculi motoneurons and interpositus neurons (kinetic parameters), and of the different types of eyelid response (kinematic parameters). This characterization was performed trial by trial, block by block, and session by session for each selected experimental animal during classical conditioning of eyelid responses.

Appendix S2. Computational algorithm of dynamic correlation
This algorithm was based on the application of a simple linear regression model, with the peculiarity that it was applied in a dynamic sequence for various correlation intervals. The model described, in statistical terms, the effect of neuronal activity (posterior interpositus neurons and orbicularis oculi motoneurons) on eyelid responses (position and velocity). The algorithm was
implemented for both conditioned (CRs) and unconditioned (URs) eyelid responses, and their respective starts were taken as the zero reference point of the dynamic correlation function (see Fig. 4A of the main text). Once the interval size was chosen, an identical time interval was selected in the instantaneous frequency, and the latter was correlated with the kinematic variables. An optimal range of 200 ms to the left and to the right of the zero reference point was established, assuming that the intervals of physiological interest were included in the correlation analysis. Finally, time-dependent coefficient correlation functions were also obtained.

In all cases, regression line coefficients (slopes and intercepts) between instantaneous frequencies (interpositus neurons and motoneurons) and eyelid responses (CRs and URs) were determined separately. This was also done for the regression lines in the global interval, which that included both types of response (CRs and URs). The corresponding statistical significance tests (Student’s t-test and F statistic) were performed for the three parameters: correlation coefficient ($r$), and slope and intercept of the regression line. These parameters were statistically significant if the resulting probability $P$ met the requirements of the hypothesis test $P < p$, where $p < 0.01$ was the predetermined statistical significance level (Belsley et al., 1980). Identical intervals were chosen for both eyelid CRs and instantaneous frequencies of interpositus neurons and orbicularis oculi motoneurons. The mean length of the intervals was within the range of 187–261 points, which corresponds to 179.51–250.55 ms. Correlation coefficients greater than 0.1238 were statistically significant, at least 95% ($P < 0.05$), according to the criterion $r > \frac{2}{\sqrt{Np}}$, where $r$ is the well-known Pearson’s product moment correlation coefficient, and $Np$ the total number of points of the correlated variables (Allen and Cady, 1982).

**The dynamic correlation functions**

In this study, dynamic correlation functions were obtained trial by trial. For the curves represented in Figure 4B of the main text, the correlation functions corresponding to the trials taken from all the blocks of the same session were averaged – session by session – for each experimental animal during classical
conditioning of eyelid responses. From these functions, a coefficient correlation matrix was obtained; and with these data, the dynamic evolution of kinetic-kinematic correlations during classical conditioning was evaluated.

Dynamic correlation functions enable the identification of the time of occurrence of the maximum correlation with respect to the zero reference point. In addition, they describe how the correlation coefficients evolved during the execution of the dynamic correlation algorithm. The value of $T.K$ with $K = C01, \ldots, C10$ which maximized the dynamic correlation function was taken as an estimation of the relative time delay between the firing activities of interpositus neurons and eyelid responses, under the implicit assumption that they were linearly related. Hence, it was possible to determine “causality” criteria, e.g., if the maximum correlation occurred before or after the start of eyelid CRs, and before or after the maximum firing rate of interpositus neurons during the conditioned stimulus-unconditioned stimulus (CS-US) interval. This analysis indicated whether or not the firing activities of interpositus neurons encoded eyelid kinematics and whether or not this activity was causally related to CR generation.

The discharge rate of interpositus neurons seemed to mirror the position and/or the velocity of eyelid CRs, and to increase during the CS-US interval in parallel with the amplitude of the learned response (Gruart and Delgado-García, 1994). According to the study presented here, the maximum instantaneous frequency ($if_{\text{max}}$) of interpositus neurons (type A; see Gruart and Delgado-García, 1994) increased during the conditioning, thus reaching mean amplitude values of $if_{\text{max}}.C01 = 151.5$ – $if_{\text{max}}.C10 = 322.6$ spikes/s in a mean time of occurrence that decreases at $t.C01 = 49.1$ – $t.C10 = 13.4$ ms after the start of eyelid CR. This increase in $if_{\text{max}}$, in association with the decrease in its mean time of occurrence, caused the maximum correlation coefficient between interpositus neuron activity and eyelid CRs to decrease: $r(\text{max}).C01 = 0.68 - r(\text{max}).C10 = 0.51$, $P < 0.01$. These maximum correlation coefficient values occurred in a mean temporal range of $T.C10 = 4.8 - T.C01 = 45.1$ ms with respect to the zero reference point. The foregoing allows us to affirm that interpositus neurons do not directly encode
eyelid kinematics; i.e., their contribution is only slightly significant in the dynamic correlation range.

The collected correlation coefficient values showed a weak coupling between neuronal activity in the interpositus nucleus and eyelid position during CRs. However, a weak correlation (i.e., $r < 0.7$) is not necessarily indicative of an absence of relationships between the variables, and nor does a high correlation necessarily indicate causality (Baccala, and Sameshima, 2001; Granger, 1980). In practice, the significance of $r_{\text{max}}$ was usually checked, at the desired level of statistical confidence, by calculating the residual cross-correlation. It must be mentioned here that the cross-correlation function at zero time lag is the linear correlation coefficient, an index frequently used to measure the linear interdependence between two variables (Allen and Cady, 1982; Belsley et al., 1980).

According to the study presented here, another important point to take into account is that the difference of $\Delta \tau = t_K - T_K$ with respect to $K = C01, \ldots, C10$ was always positive (mean difference of delay was 3.9 ms on the 1st day and 8.6 ms on the 10th day), i.e., the time of occurrence of the maximum correlation was shorter than the time of occurrence of the maximum instantaneous frequency. On the other hand, experimental evidence, such as the increase in $i_{\text{max}}$, of interpositus neurons and the decrease in the time of occurrence of $i_{\text{max}}$ after the start of CR and during classical conditioning, suggested an only slightly significant covariance between the correlated variables. It should be noticed that the dynamic correlation curves (see Fig. 4B of the main text) were rather irregular under the same experimental conditions, a fact indicating a limited (or at least an uncertain) influence of interpositus neurons on the generation of learned eyelid responses. The statistical algorithm developed here indicated that the contribution of this neuronal population can be interpreted better on the assumption that it compensates or reinforces the generation of eyelid responses. Thus, the role of interpositus neurons might be related more to the modulation of eyelid responses than to their generation.

In contrast, the dynamic correlation function for orbicularis oculi motoneurons remained quasi-stationary, and very significant mean correlation coefficient values ($r_{\text{max}}).C01 = 0.68 - r_{\text{max}}.C10 = 0.96$, with $P < 0.01$) were
computed during conditioning sessions. According to these results, motoneurons certainly encoded eyelid kinematics directly at every instant of the dynamic correlation range. This inference was supported by the experimental fact that the discharge rate of motoneurons increased progressively across the learning process, with a relative refractory period (interspike time interval) that decreased progressively during the CS-US interval and reached values slightly greater than 3 ms immediately after US presentation. Thus, a motoneuronal discharge pattern that correlated significantly with eyelid position CRs in all the conditioning sessions was obtained.

Appendix S3. Mathematical demonstration of functional dependence between the falling correlation and the phase-modulation properties of interpositus neurons

Let us assume that the simple regression models for the instantaneous frequency and eyelid position functions — considered as independent variables — are effective

\[ f_{IP}(t) = s_{IP}\dot{\theta}(t) + i_{IP} \]  
\[ f_{MN}(t) = s_{MN}\dot{\theta}(t) + i_{MN} \]  

The areas underneath the instantaneous frequency functions \( f(t) \) and the eyelid position functions \( \dot{\theta}(t) \) are expressed as

\[ I_{IP}^k = \sum_{k}^{I_k} \int_{t_{k-1}}^{t_k} f_{IP}(t) \, dt = \int_{t_0}^{t_k} f_{IP}(t) \, dt \]

\[ I_{MN}^k = \sum_{k}^{I_k} \int_{t_{k-1}}^{t_k} f_{MN}(t) \, dt = \int_{t_0}^{t_k} f_{MN}(t) \, dt \]

\[ I_{\dot{\theta}}^k = \sum_{k}^{I_k} \int_{t_{k-1}}^{t_k} \dot{\theta}(t) \, dt = \int_{t_0}^{t_k} \dot{\theta}(t) \, dt \]
where the integration intervals have been made equivalent and \( k = 1, 2, \ldots, N \), 
\( N \) being the number of components of the cumulative area vectors \( I^{MN} \), \( I^{IP} \), 
and \( I^{\theta} \). From here on, parameter \( t_0 \) will coincide with the time of occurrence of 
the first action potential for interpositus neurons, immediately after CS 
presentation. The integration range extends from \( t_0 \) to US presentation, with a 
sampling time of 0.95994 ms.

Integrating members of both equations (1) and (2), and solving 
appropriately, we obtain

\[
I^{MN}_k - I^{IP}_k = (s^{MN}_k - s^{IP}_k) I^0_k + (i^{MN}_k - i^{IP}_k) (t_k - t_0) \quad (3)
\]

\[
I^0_k = -\frac{i^{MN}_k - i^{IP}_k}{s^{MN}_k - s^{IP}_k} (t_k - t_0) + \frac{I^{MN}_k - I^{IP}_k}{s^{MN}_k - s^{IP}_k} \quad (3.a)
\]

Lemma 1: The \( k \)th component of the cumulative area vector (cumulative 
integral activity) for eyelid position \( I^{\theta} \) is a function of the slopes and 
intercepts of regression lines \( r^{p,\theta} \) and \( r^{\theta,\theta} \), and of the difference between the 
\( k \)th components of the cumulative area vectors for functions \( f_{ip}(t) \) and \( f_{mn}(t) \).

Cumulative area functions (integrated neuronal activity) \( I^{MN} \) and \( I^{IP} \) can 
intercept at one or more points, but they never descend. For that reason, their 
“oscillatory” character will depend on the relative increment of the components 
of these vectors.

Let us assume at least three components, \( k \neq p \), \( k \), and \( k + j \) with 
\( p \neq j \), satisfying the following inequalities:

\[
I^{IP}_{k-p} \leq I^{MN}_{k-p} \quad (4.a)
\]

\[
I^{IP}_k \geq I^{MN}_k \quad (4.b)
\]

\[
I^{IP}_{k+j} \leq I^{MN}_{k+j} \quad (4.c)
\]

For example, for \( I^{IP} = (0, \ldots, 5, 12, 22, 23, 30, \ldots, 35) \) and 
\( I^{MN} = (0, \ldots, 5, 15, 18, 24, 30, \ldots, 35) \), the values of the functions for the \( k \)th
components could be 22 and 18, respectively ($l^k_{ip} = 22 > l^k_{ip} = 18$). Taking $p = j = 1$, the values for components $k - p$ would be 12 and 15 ($l^k_{k-p} = 12 < l^k_{k-p} = 15$), and for components $k + j$, 23 and 24 ($l^k_{k+j} = 23 < l^k_{k+j} = 24$), thus satisfying inequalities (4).

Let us find the relationships between two components satisfying inequalities (4), e.g., components $k$ and $k + j$:

$$l^k_{k} - l^k_{k} = (s_{mn} - s_{ip})l^0_k + (i_{mn} - i_{ip})(t_k - t_0) \leq 0 \quad \text{according to (4.b)} \quad (5)$$

$$l^k_{k+j} - l^k_{k+j} = (s_{mn} - s_{ip})l^0_{k+j} + (i_{mn} - i_{ip})(t_{k+j} - t_0) \geq 0 \quad \text{according to (4.c)} \quad (6)$$

Multiplying (5) by -1 and adding (6), we get

$$(l^0_{k+j} - l^0_k)(s_{mn} - s_{ip}) + (t_{k+j} - t_k)(i_{mn} - i_{ip}) \geq 0 \quad (7.a)$$

Lemma 2: The relative increment between components $k$ and $k + j$ of the cumulative area vector for eyelid position $l^\theta$ depends on the relative increment between the characteristic times for these components and on the slopes and intercepts of regression lines $r_{0, mn}$ and $r_{0, ip}$, according to inequality (7.a). Therefore, cumulative areas $l^mn$ and $l^ip$ intercept once between characteristic times $t_k$ and $t_{k+j}$.

For (4.a) in relation to (4.b), we see that

$$(l^0_{k-p} - l^0_k)(s_{mn} - s_{ip}) + (t_{k-p} - t_k)(i_{mn} - i_{ip}) \geq 0 \quad (7.b)$$

Adding (7.a) and (7.b) together, we obtain

$$(s_{mn} - s_{ip})[(l^0_{k+j} - l^0_k) + (l^0_{k-p} - l^0_k)] + (i_{mn} - i_{ip})[(t_{k+j} - t_k) + (t_{k-p} - t_k)] \geq 0 \quad (8)$$
Lemma 3: The relative increment between components \( k - p \) and \( k \), and between \( k \) and \( k + j \) of the cumulative area vector for eyelid position \( I^\delta \) depends on the relative increment between the characteristic times for these components and on the slopes and intercepts of regression lines \( r_{\delta, MN} \) and \( r_{\delta, IP} \), according to inequality (8). Consequently, cumulative areas \( I^{MN} \) and \( I^{IP} \) intercept once between characteristic times \( t_{k-p} \) and \( t_k \), and again between characteristic times \( t_k \) and \( t_{k+j} \).

In (7) and (8), equality is satisfied when the same components of cumulative area vectors \( I^{MN} \) and \( I^{IP} \) are equal. In this case, equation (9), obtained on this assumption from equation (3.a), must be verified:

\[
l^0_k = \frac{-i_{MN} - i_{IP}}{s_{MN} - s_{IP}} (t_k - t_0)
\]  

(9)

Another interesting relationship is the one estimating the relative increment between components of the same function:

\[
l^0_k = s_{IP} l^0_k + i_{IP}(t_k - t_0), \quad l^0_{k+j} = s_{IP} l^0_{k+j} + i_{IP}(t_{k+j} - t_0)
\]

\[
l^0_{k+j} - l^0_k = s_{IP}(l^0_{k+j} - l^0_k) + i_{IP}(t_{k+j} - t_k)
\]

\[
l^{MN}_k = s_{MN} l^0_k + i_{MN}(t_k - t_0), \quad l^{MN}_{k+j} = s_{MN} l^0_{k+j} + i_{MN}(t_{k+j} - t_0)
\]

\[
l^{MN}_{k+j} - l^{MN}_k = s_{MN}(l^0_{k+j} - l^0_k) + i_{MN}(t_{k+j} - t_k)
\]

from which we obtain

\[
l^0_{k+j} - l^0_k = -\frac{i_{MN}}{s_{MN}} (t_{k+j} - t_k) + \frac{l^{MN}_{k+j} - l^{MN}_k}{s_{MN}}
\]  

(10.a)

\[
l^0_{k+j} - l^0_k = -\frac{i_{IP}}{s_{IP}} (t_{k+j} - t_k) + \frac{l^{IP}_{k+j} - l^{IP}_k}{s_{IP}}
\]  

(10.b)

On the basis of expressions (10), we conclude that
\[
\frac{l_{k+j}^{MN} - l_{k}^{MN}}{s_{MN}} - \frac{l_{k+j}^{IP} - l_{k}^{IP}}{s_{IP}} = \left[ \frac{i_{MN}^{k} - i_{IP}^{k}}{s_{MN}^{k} - s_{IP}^{k}} \right] (t_{k+j} - t_{k}) \tag{11}
\]

Having determined the dependent relationships of the intercepts and slopes of the simple regression models, we will now analyze these relationships for the following multiple regression model:

\[
f_{MN}(t) = \hat{a}_0 + \hat{a}_t \dot{e}(t) + \hat{a}_2 f_{IP}(t) + u(t) \tag{12}
\]

Integrating in (12) according to the same procedure applied before, we see that

\[
l_{k}^{MN} = \hat{a}_0 (t_k - t_0) + \hat{a}_t l_{k}^\dot{e} + \hat{a}_2 l_{k}^{IP} + \hat{u}_k \tag{13}
\]

and substituting expressions \(l_{k}^{MN} = s_{MN} l_{k}^\dot{e} + i_{MN} (t_k - t_0)\), \(l_{k}^{IP} = s_{IP} l_{k}^\dot{e} + i_{IP} (t_k - t_0)\) in (13), we obtain

\[
l_{k}^\dot{e} = \frac{\hat{a}_0 + \hat{a}_2 i_{IP} - i_{MN}}{\hat{a}_t + \hat{a}_2 s_{IP} - s_{MN}} (t_k - t_0) + \hat{U}_k \tag{14.a}
\]

\[
l_{k}^\dot{e} = \frac{\hat{a}_0 + \hat{a}_2 i_{MN} - i_{IP}}{\hat{a}_t + \hat{a}_2 s_{MN} - s_{IP}} (t_k - t_0) + \hat{U}_k \tag{14.b}
\]

According to equations (3), (7), (8), and (14), there is a mathematical dependence between the parameters of the simple or multiple regression model and the estimated values of the cumulative area vector components for eyelid position \(l_{k}^\dot{e}\). Hence, the relative variations of these components (see Fig. 7) depend not only on the relative variations of functions \(f_{IP}(t)\) and \(f_{MN}(t)\), but also on how and to what extent they encode eyelid position \(\dot{e}(t)\) in the integration interval (see Fig. 4B).

**Appendix S4. Relationships between interpositus neuron firing and the percentage of CRs across conditioning**
The maximum instantaneous frequency (if max.) of interpositus neurons increased across conditioning (Fig. S2A of the Supplemental Data), whilst their mean time of occurrence decreased up to values closed to the start of eyelid CRs. This increase in if max. (Fig. S2B, line e2(if max., % CRs)), together with the decrease in its mean time of occurrence, caused the maximum correlation coefficient between interpositus neuron activity and eyelid CRs to decrease (Fig. S2B, line e1(if max., r max.)). The time of occurrence of this maximum correlation coefficient also decreased across conditioning, but always lagged CR start. Thus, interpositus neurons did not directly encode eyelid kinematics; i.e., their contribution was slightly significant in the dynamic correlation range (Fig. 4B of the main text). These facts denote the falling correlation property of cerebellar interpositus nucleus (Fig. 5A, B of the main text). Likewise, the increase in if max., and the decrease in its mean time of occurrence caused the cumulative integrated function, corresponding to interpositus neurons, to oscillate by progressively inverting phase information (Fig. 7A-D of the main text). We have interpreted the above results as a phase modulation property of cerebellar interpositus nucleus. The falling correlation and phase modulation properties of cerebellar interpositus nucleus in the dynamic control of CRs are not functionally dissociated (Appendix S3, in Supplemental Data). There is a mathematical dependence between the simple and multiple regression model parameters and the estimated values of the integrated eyelid position activity components. Hence, the relative variations of these components depended not only on the relative variations of the instantaneous frequency of interpositus neurons and orbicularis oculi motoneurons, but also on how and to what extent they encoded eyelid position during CRs (Fig. 6A, B of the main text). In addition, the dynamic correlation function for orbicularis oculi motoneurons was kept quasi-stationary with high mean correlation coefficient values across conditioning sessions (Fig. 6B of the main text). Taking this into account, orbicularis oculi motoneurons certainly encode eyelid kinematics directly at every instant of the dynamic correlation range. Thus, a discharge pattern for orbicualris oculi motoneurons that correlates significantly with eyelid position during CRs in all the conditioning sessions was obtained. These considerations allow us to confirm that orbicularis oculi motoneurons generate the natural oscillatory properties of the neuromuscular elements involved in eyelid
kinematics, and to conclude that interpositus neurons play a modulating role in the dynamic control of learned motor responses; i.e., that they could be considered as a neuronal phase-modulating device.
References


Table S1. The characteristic values of the hierarchical clustering algorithm

<table>
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<tr>
<th>Characteristic</th>
<th>Value</th>
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<td>Optimal method</td>
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</tr>
<tr>
<td>Significant clusters</td>
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</tr>
</tbody>
</table>
Legends for Figures included in the Supplemental Data

Figure S1. A diagrammatic representation of the experimental design and of data processing. A, The first data-processing stage includes all trials (with and without CRs, n = 10) from all the experimental blocks (n = 12) of all conditioning sessions (n = 15, H01-H02, C01-C10, E01-E03) and for all of the experimental cats (n = 7; 3 of the animals were used for recordings at the facial nucleus, whereas the other 4 were used for recordings at the cerebellar interpositus nucleus). The total number of recorded orbicularis oculi motoneurons (MN = 110), and of type A (n = 131) and type B (n = 43) interpositus neurons are also indicated. B, In the following stage, the analysis was restricted to 5 cats and a pre-clustering algorithm was applied (trial to trial and block to block) for the 36 kinematic parameters included in this study. For the sake of homogeneity, only 90 MNs and 90 type A interpositus neurons were included in this analysis. C, An example of the possible combinations (corresponding to the \( p \)-th block of the \( i \)-th session) in order to form adequate global files for the 5 experimental animals included in this analysis. Blue squares represent the 10 trials per block for cats 01, 02, and 03 (interpositus nucleus recordings), whereas magenta squares represent corresponding trials and blocks for cats 05 and 06 (facial nucleus recordings). Since for the first trial of each block the CS is presented alone (*) its possible combinations were not considered for this study. Squares including the same letter (A-Z) represent a combination between an IP partial file and an MN partial file in order to form a global file per trial. In the illustrated example appeared a total of 16 global files (illustrated by red letters). Green letters (n = 5) illustrate trials including type B interpositus neurons (rejected for further analysis as indicated in B). Black letters (n = 6) indicate trials which kinematic properties were significantly different from the rest of trials of the corresponding block and session. D, E. At this stage only trials including CRs were considered. Global files were averaged as indicated in Appendix S1 of this Supplemental Data to form the averaged blocks to be further processed with the multivariate cluster analysis including the 60 selected parameters (24 kinetic and 36 kinematic). In E is indicated the correspondence between the dynamic correlation functions carried out automatically for the 5 cats (63 MNs and 71 type A interpositus neurons) indicated in B with the same functions applied
(without cluster analysis) to data collected from the 2 animals (19 MNs and 19 interpositus neurons) reserved as controls.

Figure S2. Relationships between type A interpositus neuron firing rates and the percentage of CRs across the 10 conditioning sessions. A, Learning curve (blue circles; mean (± S.E.M.) corresponding to animals (01, 02, and 03) included in the cluster analysis indicated in Figs. 3A (main text) and S1D (Supplemental Data). The mean (± S.E.M.) firing rate of 71 identified interpositus neurons (blue squares) during the CS-US interval is also indicated. B, The abscissa and the left ordinate illustrates the relationship between the peak firing rate (if max.) of interpositus neurons (blue squares; e₂ regression line) and the percentage of conditioned responses. The abscissa and the right ordinate illustrates the relationship between peak firing rate and the coefficient of correlation (red triangles; r max. coefficient; e₁ regression line) with eyelid performance during CRs, across conditioning. Note that the increase in if max. (e₂ regression line) together with the decrease in its time of occurrence, caused a decrease in the r max. coefficient between interpositus neurons activity and eyelid CRs (e₁ regression line).