

# Modelling mechanochemical coupling in optogenetically activated cell layers

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In adherent cells, actomyosin contractility is regulated mainly by the RhoA signaling pathway, which can be controlled by optogenetics. To model the mechanochemical coupling in such systems, we introduce a finite element framework based on the discontinuous Galerkin method, which allows us to treat cell doublets, chains of cells and monolayers within the same conceptual framework. While the adherent cell layer is modeled as an actively contracting viscoelastic material on an elastic foundation, different models are considered for the Rho-pathway, starting with a simple linear chain that can be solved analytically and later including direct feedback that can be solved only numerically. Our model predicts signal propagation as a function of coupling strength and viscoelastic time scales and identifies the conditions for optimal cell responses and wave propagation. In general, it provides a systematic understanding of how biochemistry and mechanics simultaneously contribute to the communication of adherent cells.

cell mechanics | optogenetics | signal propagation | mechanochemical coupling | finite element method

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## Introduction

With the advent of mechanobiology, it has become clear that biochemistry and mechanics play an equally important role for the function of cellular systems (1, 2). For example, it has been shown that stem cells actively sense the stiffness of their environment, and that this mechanical input together with soluble factors determines their subsequent differentiation (3, 4). Later it has been shown that one important element is the transcription factor Yes-associated protein (YAP), which is activated on stiff substrates and in geometrical confinement (5, 6).

A close coupling between biochemistry and mechanics also exists for multicellular systems. For example, it has been shown that in wound healing and infection, neighboring epithelial cells coordinate their activity by mechanical activation of extracellular signal-regulated kinases (ERK) (7, 8). A mathematical model demonstrated how wave propagation results from mutual feedback between mechanics and biochemistry: leader cells pull on their followers, ERK is activated in the followers and activates contractility, which leads to forces on the next row of followers (9, 10). A similar mechanism is also realized by the tumour suppressor protein merlin, which under mechanical force is relocalized from the cell-cell junctions to the cytoplasm (11). Interestingly, the mechanism for wave propagation is similar to the one for action potentials in the neurosciences. In principle, the signal could go both

ways, but a refractory period in the sending part prevents the wave from going backwards.

The general scheme of mechanochemical feedback leading to complex systems behaviour is even more evident for developing organisms (12, 13). Here morphogen concentration fields determine where cells grow and divide, and this leads to changes of the domain in which signaling is active, which in turn changes the way morphogens are secreted and distributed. Such feedback loops lead to non-linear systems dynamics which can explain the intricate patterns that emerge during tissue formation and embryogenesis (12). One prominent model organism is the fruit fly Drosophila, where experimental observations have been coupled with mathematical models (14, 15). Another one is the freshwater polyp Hydra, which is able to regenerate its patterning even after being cut in pieces (16–18). However, for such organismal systems it is very challenging to achieve a systems level understanding connecting molecular processes to the tissue scale. For mechanistic understanding, it is therefore rewarding to turn back to their elementary building blocks, the cells, and small assemblies of such cells, with the long term aim to upscale to larger systems.

To understand the coupling of biochemistry and mechanics at the level of single cells, one must start with the actin cytoskeleton (19–21). This is a network of actin filaments and myosin II molecular motor proteins that determine the mechanical properties of cells, particularly during processes such as adhesion, migration, and division. Since the actin cytoskeleton continuously consumes energy in the form of adenosine triphosphate (ATP) to grow and reorganize its filaments, generating forces and flows in the process, the appropriate modeling approach is to introduce active stresses that are coupled to the chemical potential of the myosin II motors. This central concept led to the development of active gel theory (22, 23). Active gel theory is commonly used to model single-cell migration (24, 25), but can also be readily extended to larger systems, such as tissue flow (26).

To incorporate more mechanistic details into the process of force generation by cells, one must also consider how it is regulated by the small GTPases from the Rho-family, including RhoA, Rac1 and Cdc42 (21, 27). Briefly, Rac1 and Cdc42 primarily regulate the assembly of larger protrusive actin structures, such as lamellipodia and filopodia, respectively, while RhoA is predominantly responsible for the formation of actomyosin contractility. The activity of these small GTPases is controlled by many different Guanine Exchange Fac-

tors (GEFs). If such a GEF activates RhoA, this in turn activates Diaphanous-related formin (Dia) for actin polymerization and Rho-associated protein kinase (ROCK) for contractility through myosin II molecular motors (28). Together, these effects then lead to productive force generation.

Several positive and negative feedback loops exist among these components, leading to complex temporal dynamics and pattern formation (21, 27). For instance, Bement et al. (29) identified an activator-inhibitor relationship between RhoA and F-actin, which results in the emergence of spiral contraction waves during cytokinesis in *Xenopus* embryonic cells. Similar surface contraction waves have been observed in starfish oocytes during maturation, modeled by the coupled reaction kinetics of actin and myosin II (30, 31). In a systematic study, by combining nonlinear system dynamics and experimental data, Kamps et al. (32) developed a detailed model for the reaction kinetics of GEF, RhoA, and myosin II. This model not only demonstrates the complexity of the RhoA pathway, but also successfully explains the experimental observations of pulsatile contractions in the actin cortex, identifying cytosolic GEFH1 as a crucial parameter for the emergence of this pulsatile behavior.

While GEFs for the small GTPases from the Rho-family sometimes are activated purely by biochemical pathways, often their activation results from mechanical forces (33–35), similar to the cases of ERK (7, 9, 10) and merlin (11). Often, theoretical models incorporate these concepts by proposing feedback mechanisms between mechanical tension and biochemical signaling. For example, a positive biochemical-mechanical feedback loop between forces exerted on focal adhesions and RhoA signaling at these sites can explain spatial gradients in the periodic myosin- $\alpha$ -actinin pattern in stress fibers stimulated with calyculin A (36). Several mathematical studies combined simple models for Rho GTPase activity and cell mechanics to demonstrate that their interplay leads to complex cell behaviors (37, 38). The authors showed that their proposed system can exhibit bistability, where the two states represent permanently contracted or relaxed cells, and can also produce oscillatory states. Recently, Staddon et al. (39) coupled a basic activator-inhibitor reaction-diffusion system, comprising RhoA as the activator and myosin II as the inhibitor, with the mechanics of viscoelastic solids and fluids. In this model, the interplay between biochemistry, actomyosin contractility, and viscoelastic deformation leads to the emergence of propagating pulsatile contractions and topological turbulence in flows of RhoA.

In order to dissect these signaling pathways experimentally, one usually works with inhibitors, which are small chemical molecules that reduce the effect of certain components like ROCK or myosin II. However, the concomitant results are often rather qualitative in nature and it is not always clear how well the inhibitor reaches its putative target. Recently, optogenetics has emerged as a powerful alternative, which leads to more quantitative results (40). In optogenetics, a light-sensitive construct is engineered into the cells and can then be activated with high temporal and spatial resolution. Among

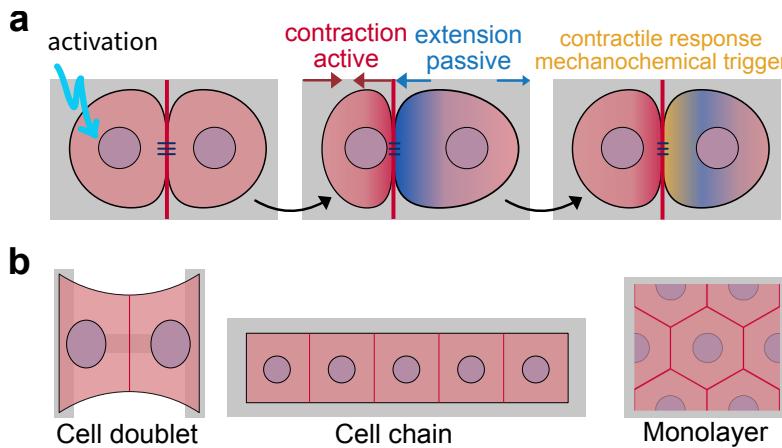
others, this approach has been applied in several studies for example to control neural activity (41), the regulation of gene expression (42, 43) or even to regulate engineered metabolic pathways in cells (44), which illustrates the versatility of this method. In the field of mechanobiology it has become an established technique to activate the Rho-pathway by recruiting a GEF to the membrane (31, 45–47), thus allowing for a precise spatiotemporal control of cytoskeletal dynamics of single cells (48) and multicellular systems (49, 50).

The quantitative advances achieved by optogenetics now open the door for a more detailed mathematical modelling of the underlying processes. Different modelling frameworks have been applied before to couple biochemistry and mechanics. One attractive option is the cellular Potts model, which has been applied to both Rho/Rac-signaling (51) and EKR-signaling (7). However, the framework is not able to model active stresses in detail. Here we therefore turn to active continuum mechanics, which is the natural framework to describe local active stresses, as demonstrated by the success of active gel theory (22–26). For the signaling pathways, we rely on a description in terms of a system of reaction-diffusion equations (32) solved on a geometrical domain which represents a cell ensemble strongly adhered to an elastic foundation (48, 52, 53). Because both frameworks, continuum mechanics and reaction-diffusion systems, lead to partial differential equations (PDEs), we turn to the finite element method (FEM), which is a standard way to numerically solve PDEs. Because in addition we also aim for multicellular systems, we specifically implement the discontinuous Galerkin finite element method, because it offers a natural way to represent the discontinuities at the cell-cell boundaries in multicellular systems. Here we first lay the conceptual basis for such an approach and then present representative applications for mechanochemical pattern formation in multicellular systems controlled by optogenetics.

The manuscript is structured as follows. First we will introduce the main concepts and equations, motivated by recent experiments on optogenetic activation of cell doublets (49). Our starting point is the observation that optogenetic activation of contractility in one cell triggers an active response in a neighboring cell, compare Fig. 1a. For Rho-activation, we start with a simple linear variant of the pathway, which is sufficient to describe the recent experiments. We then explore the consequences of this response, going from the cell doublet on a H-pattern to increasingly larger systems, namely cell chains and monolayers as commonly used in experiments (49, 50), compare Fig. 1b. Finally, we will demonstrate the generality of the simulation framework by addressing the case of a monolayer with a more dynamic model for the reaction kinetics of the Rho-pathway (32).

## Model

**Coupling biochemistry and mechanics.** Our theoretical model is strongly motivated by recent experiments on cell doublets on a H-pattern whose contractility is activated in the left cell by Rho-optogenetics, such that one can follow the response of the right cell in quantitative detail (49). The for-



**Fig. 1.** Mechanochemical coupling in different geometries. (a) Cells in contact with each other communicate through mechanochemical coupling. In the cell doublet, the optogenetically controlled contraction of the left cell induces an active contractile response in the right cell. (b) For spatial modelling, we start with the cell doublet on an H-pattern and then continue to cell chains and cell monolayers.

mulation of the model follows the central observation that actively generated stresses within the cell layer depend on the concentration of the downstream output of the RhoA-pathway. Assuming that sufficient amounts of actin filaments are generated by the Dia-leg, this is mainly the amount of active myosin II generated by the ROCK-leg of the pathway. The spatio-temporal distribution of actively generated stresses depends also on the reaction kinetics and diffusive properties of all upstream signalling proteins. The active stresses may then lead to deformation of the cell which directly feeds back to the reaction-diffusion system by generating advection terms and changing concentrations. Consequently, the spatiotemporal evolution of a signaling protein concentration  $c_i(\mathbf{x}, t)$  is described by a reaction-diffusion-advection equation on a two-dimensional time-dependent domain  $\Omega(t)$ ,

$$\frac{\partial c_i}{\partial t} + \nabla \cdot (\mathbf{v}(\mathbf{x}, t)c_i) = \nabla \cdot (\mathbf{D}\nabla c_i)) + R_{c_i}(t), \quad (1)$$

where  $\mathbf{D}$  denotes the two-dimensional diffusion tensor,  $R_{c_i}$  the reaction kinetics and the index  $i$  represents a signaling protein in the RhoA pathway. Eq. (1) arises naturally by demanding local mass conservation on the time-dependent domain by following Reynold's transport theorem. It includes an advection term  $\mathbf{v} \cdot \nabla c_i$  due to flows induced by contraction and expansion and an enrichment/dilution term  $c_i \nabla \cdot \mathbf{v}$  due to local volume changes, where  $\mathbf{v}(\mathbf{x}, t)$  corresponds to the velocity of the deforming material. Hence, deformations naturally interfere with the spatiotemporal evolution of the protein concentrations. Eq. (1) is written in terms of spatial (Eulerian) coordinates  $\mathbf{x}$  which is a convenient choice for the description of diffusion processes.

However, the deformation of the cell domain is better treated in terms of referential (Lagrangian) coordinates  $\hat{\mathbf{x}}$ . The two coordinate systems are related by the deformation field  $\hat{\mathbf{u}}(\hat{\mathbf{x}}, t) = \mathbf{x}(\hat{\mathbf{x}}, t) - \hat{\mathbf{x}}$ . We use Piola's identity  $\hat{J}\nabla \cdot \mathbf{a} = \hat{\nabla} \cdot (\hat{J}\hat{\mathbf{F}}^{-1}\hat{\mathbf{a}})$ , where  $\mathbf{a}$  is an arbitrary vector field and  $\hat{\mathbf{F}} = \partial \mathbf{x} / \partial \hat{\mathbf{x}} = \mathbf{I} + \hat{\nabla} \hat{\mathbf{u}}$  the deformation gradient tensor with  $\hat{J} = \det(\hat{\mathbf{F}})$ , to pull Eq. (1) back to the reference configuration  $\Omega_0$  and express it in terms of Lagrangian coordinates as

$$\frac{\partial}{\partial t}(\hat{J}\hat{c}_i) - \hat{\nabla} \cdot (\hat{J}\mathbf{D}\hat{\mathbf{C}}^{-1}\hat{\nabla}\hat{c}_i) - \hat{J}R_{\hat{c}_i}(t) = 0. \quad (2)$$

Here,  $\hat{\nabla}$  denotes the derivative with respect to Lagrangian coordinates,  $\mathbf{D} = D\mathbf{I}$  is assumed to be an isotropic tensor with scalar diffusivity  $D$  and  $\hat{\mathbf{C}} = \hat{\mathbf{F}}^T \hat{\mathbf{F}}$  denotes the Cauchy-Green deformation tensor. The velocity of the material is absorbed into the time-derivative in the first term. For the details of this derivation we refer to the supporting information. From the first term in Eq. (2) we see that compression ( $\partial_t \hat{J} < 0$ ) and dilation ( $\partial_t \hat{J} > 0$ ) of the elastic domain effectively alters the reaction kinetics. Further, we see that the diffusion is impacted by local deformations and can become anisotropic. Following earlier work on cells as active materials, we describe the mechanics of the cell layer as a viscoelastic continuum with active stresses coupled to an elastic foundation (48, 52, 54, 55) (compare Fig. 2a). We further assume that the lateral extent of the cell layer is much larger than its average height  $h_c$ . This allows to obtain a two-dimensional model by having conditions for plane-stresses within the elastic sheet. The force balance equation then reads

$$\nabla \cdot \boldsymbol{\sigma} + \mathbf{f} = 0, \quad (3)$$

where  $\boldsymbol{\sigma}$  is the two-dimensional in-plane Cauchy stress tensor and  $\mathbf{f}$  denotes an externally applied two-dimensional body force. The two-dimensional stress tensor is obtained by averaging the three-dimensional stress tensor over the thickness of the cell layer.

For the cell layer, we assume a linear viscoelastic constitutive relation of the solid (Kelvin-Voigt) type. Although cells are very dynamic and often are modelled by viscoelasticity of the fluid (Maxwell) type, especially in active gel theory (23), here we consider stably adhering cells that effectively behave as solids due to homeostatic mechanisms, including volume control. The Kelvin-Voigt law reads

$$\boldsymbol{\sigma}_p = \left(1 + \tau_c \frac{\partial}{\partial t}\right) (\lambda \text{tr}(\boldsymbol{\varepsilon})\mathbf{I} + 2\mu\boldsymbol{\varepsilon}), \quad (4)$$

where  $\boldsymbol{\varepsilon} = (\nabla \mathbf{u} + \nabla \mathbf{u}^T)/2$  denotes the infinitesimal strain tensor and  $\tau_c = \eta_c/E_c$  is the relaxation time defined by the ratio of viscosity  $\eta_c$  and Young's modulus  $E_c$  of the cell. Further, we introduce the two-dimensional Lamé coefficients as

$$\lambda = \frac{\nu_c h_c E_c}{1 - \nu_c^2}, \quad \mu = \frac{h_c E_c}{2(1 + \nu_c)}, \quad (5)$$

where  $\nu_c$  is the cellular Poisson's ratio.

Actomyosin contractility is modeled by an active stress tensor  $\sigma_a$  and the total cell stress is given by the sum of the passive and active contributions,  $\sigma = \sigma_p + \sigma_a$ . The cell layer is coupled to an elastic substrate which can be thought of as a continuous layer of springs between the cell and a rigid substrate (52, 56). In particular, the elastic foundation can also describe an elastic substrate as commonly used in traction force microscopy. It is described by a local force per unit area

$$\mathbf{f} = -Y\mathbf{u}, \quad (6)$$

where  $Y$  is the spring constant density ( $[Y] = \text{N m}^{-3}$ ) and  $\mathbf{u}$  the displacement field of the cell layer. In case of a micropatterned surface, the spring constant density becomes position dependent and defines the adhesion geometry. Note that  $\sigma$  measures stresses in the deformed configuration and is evaluated at spatial coordinates. This means that in order to express Eq. (3) in terms of referential coordinates one has to use the first Piola-Kirchhoff stress tensor  $\hat{\mathbf{P}}$ . This distinction becomes important only in the limit of finite strains. In the limit of small strains, i.e. small deformation gradients, we can assume  $|\hat{\nabla}\hat{\mathbf{u}}| \ll 1$  and only consider terms up to linear order in  $\hat{\nabla}\hat{\mathbf{u}}$  for which we can approximate  $\hat{\mathbf{F}}^{-1} \approx \mathbf{I} - \hat{\nabla}\hat{\mathbf{u}}$ ,  $\hat{J} \approx 1 + \text{tr}(\hat{\nabla}\hat{\mathbf{u}})$  and  $\hat{\mathbf{C}} = \mathbf{I} + \hat{\nabla}\hat{\mathbf{u}} + \hat{\nabla}\hat{\mathbf{u}}^\top + \mathcal{O}(|\hat{\nabla}\hat{\mathbf{u}}|^2) \approx \mathbf{I} + 2\varepsilon$ . Given this small strain assumption, the two tensors only differ in terms  $\mathcal{O}(|\hat{\nabla}\hat{\mathbf{u}}|^2)$ , such that  $\sigma \approx \hat{\mathbf{P}}$ . We will use referential coordinates for the force balance and constitutive relation, respectively.

The boundary of the cells is non-permeable for the signaling proteins and hence, we impose zero-flux boundary conditions at the interface between cell interior and cell exterior  $\mathbf{j} \cdot \mathbf{N} = 0$  on  $\partial\Omega_0$  with  $\mathbf{j} = \hat{J}\mathbf{D}\hat{\mathbf{C}}^{-1}\hat{\nabla}\hat{c}_i$  being the diffusive flux. Besides ensuring mechanical integrity, an inherent feature of intercellular junctions, e.g. tight junctions, is to maintain compartmentalisation in tissues by acting as a barrier for fluids and solutes. Therefore also the cell-cell junctions are non-permeable, which is incorporated by imposing an internal zero-flux boundary condition on  $\Gamma_{\text{CCJ}}$ . As no external stresses are applied at the boundary  $\partial\Omega_0$  of the sheet, we have the boundary condition  $\sigma \cdot \mathbf{N} = 0$  on  $\partial\Omega_0$ . The net traction force exerted by the cell layer vanishes as  $\int_{\Omega_0} Y\mathbf{u} d\Omega_0 = 0$ , as required for a closed system.

In summary, the model can be formulated as follows: Find the displacement field  $\mathbf{u}$  together with the concentrations  $\hat{c}_i$  of the signaling species such that

$$\nabla \cdot \sigma = Y\mathbf{u} \text{ in } \Omega_0, \quad (7)$$

$$\frac{\partial}{\partial t}(\hat{J}\hat{c}_i) - \hat{\nabla} \cdot (\hat{J}\mathbf{D}\hat{\mathbf{C}}^{-1}\hat{\nabla}\hat{c}_i) - \hat{J}R_{\hat{c}_i}(t) = 0 \text{ in } \Omega_0, \quad (8)$$

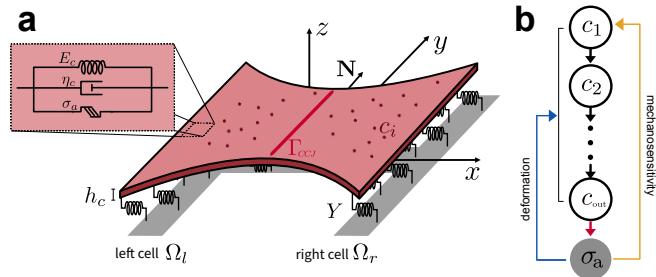
together with the boundary conditions

$$\sigma \cdot \mathbf{N} = 0 \text{ on } \partial\Omega_0, \quad (9)$$

$$-\hat{J}\mathbf{D}\hat{\mathbf{C}}^{-1}\hat{\nabla}\hat{c}_i \cdot \mathbf{N} = 0 \text{ on } \partial\Omega_0, \quad (10)$$

$$-\hat{J}\mathbf{D}\hat{\mathbf{C}}^{-1}\hat{\nabla}\hat{c}_i \cdot \mathbf{N}_{\text{CCJ}} = 0 \text{ on } \Gamma_{\text{CCJ}}. \quad (11)$$

In addition to the geometrically arising coupling between the RD-system and mechanics as described by Eqs. (7, 8), we



**Fig. 2.** Mechanocomplex model for a cell doublet. (a) A cell doublet of thickness  $h_c$  stably adheres to an elastic foundation via springs that are homogeneously distributed over the area defined by the H-shaped micropattern. The cell doublet (Young's modulus  $E_c$ , viscosity  $\eta_c$ ) is characterised by a cell-cell junction ( $\Gamma_{\text{CCJ}}$ ) separating the two cells ( $\Omega_l, \Omega_r$ ) along the vertical symmetry axis of the micropattern ( $y$ -axis). The elastic properties of the cell are sketched in the inset. The elastic substrate is described via the spring stiffness density  $Y$ . (b) The simplest model for the signaling cascade is a linear chain in which mechanosensitivity leads to activation of the first signaling protein and the last signaling protein determines active stresses. All other signaling proteins experience a natural feedback resulting from deformation of the cell domain during contraction.

introduce two additional coupling mechanisms as schematically illustrated in Fig. 2b. First, we couple the output of the RD-system, i.e. the concentration of the last signaling protein of the activation cascade  $c_{\text{out}}$ , to active stresses  $\sigma_a$  (red arrow in Fig. 2b). For this we relate  $\hat{c}_{\text{out}}(\hat{x}, t)$  to  $\sigma_a$  via a relation (39, 57)

$$\sigma_a(\hat{c}_{\text{out}}) = \sigma_0 \tanh(S\hat{c}_{\text{out}}), \quad (12)$$

where  $\sigma_0$  is the maximal contractile stress and  $S$  a parameter which controls how sensitive stress generation is. Since  $\tanh(x) \leq 1$  everywhere, we additionally ensure that active stresses are bound and hence avoid numerical instabilities. Second, we introduce mechanosensitivity by relating the mechanical perturbations to the activation of the most upstream signaling protein  $\hat{c}_1$  in the reaction-diffusion system, see Fig. 2b (yellow arrow). In our model, the mechanical perturbation can either be force-related (measured in terms of internal stresses) or deformation-related (expressed in terms of strain or compression/stretch). From the perspective of continuum mechanics, these measures are provided by the Cauchy stress tensor  $\sigma$  and the Cauchy strain tensor  $\varepsilon$  (or the deformation gradient tensor  $\mathbf{F}$ ). To make this coupling independent of the frame of reference, for each of the different measures we can choose between two tensor invariants (for a 2D system), the trace or the determinant (58). Motivated by experimental studies in a strain-controlled experimental setup, showing that cells respond directly to stretch (59), we decide to introduce a strain-dependent feedback. Without specifying a specific RD-system, we assume an activation rate of the first signaling protein due to passive strains via a source term of the form

$$\partial_t \hat{c}_1 = a_{c_1} \text{tr}^+(\varepsilon), \quad (13)$$

where  $a_{c_1}$  is a generic activation rate which might depend on other quantities depending on the specific choice for the RD-system (similar to Hino et al. (7)). The plus sign indicates that coupling is only present in regions of positive strains, i.e.  $\text{tr}^+(\varepsilon) := \max(0, \text{tr}(\varepsilon))$ . We want to emphasize that the magnitude of  $a_{c_1}$  has to be chosen such that if

multiplied by  $\text{tr}^+(\varepsilon)$  it results in an appropriate rate for the strain-dependent feedback.

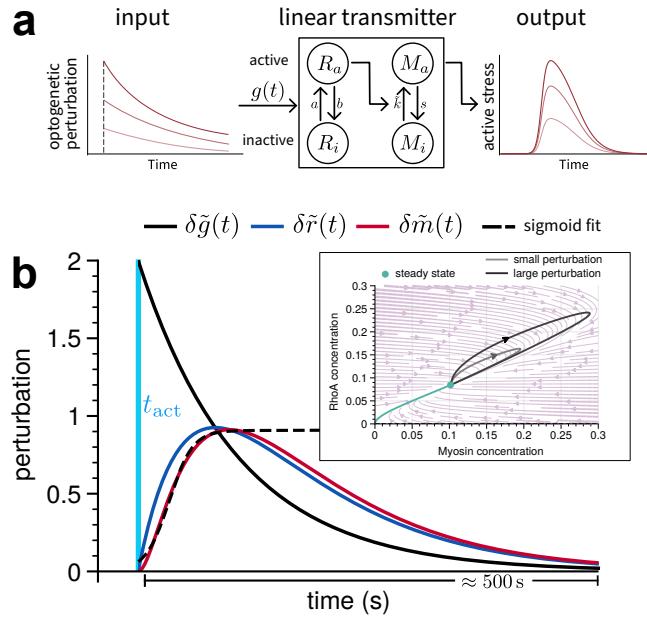
**Simple model for the Rho-pathway with optogenetic activation.** Although the RhoA-pathway allows for complex dynamics, earlier work has shown that at least in cells with strong adhesion, the actin cytoskeleton is regulated in the vicinity of a stable fixed point of this pathway (48, 49). One aspect could be that strongly adherent cells exhibit dominant stress fibers. Since stress fibers are highly organized structures, it is plausible to assume a differently organized reaction-diffusion system than for e.g. the homogeneous actin cortex in egg cells (29). Indeed it has been shown recently that different organizations of the actin cytoskeleton lead to different activation and relaxation times in the Rho-pathway (48). Another aspect might be the observation that the stability of the RhoA-pathway has a strong dependence on the total GEF-concentration (32). This suggests that the total GEF expression levels, which are naturally elevated in cells transfected with an optogenetic construct, render their RhoA-system more stable. Since cells transfected with the CRY2/CIBN system show a significantly higher baseline contractility, we assume that this might correspond to the stable branch of high GEF-concentrations (32).

First, we want to focus on this regime and describe optogenetic activation as a reversible process such that after activation cells eventually go back to their homeostatic contractility level without showing any significant oscillatory or excitable behavior upon photoactivation. Excitability is therefore completely controlled by the recruitment of a GEF to the membrane and can be scaled by the duration of the activation light pulse until saturation sets in (45, 46). Motivated by these observations, we first assume a linear input-output relationship between GEF plasma membrane recruitment and myosin II induced contractility. This assumption not only reduces the number of unknown parameters, it also allows for an analytical solution of the homogeneous system, such that it can be fully understood. Our proposed RhoA-myosin reaction scheme is shown in Fig. 3a. GEF activity enters implicitly through a predefined input signal which we describe by a function

$$g(t) = g_{ss} + g_a e^{-\lambda(t-t_{act})} H(t - t_{act}) = g_{ss} + \delta g(t). \quad (14)$$

Here  $g_{ss}$  represents a normalized steady-state GEF concentration (fraction of active GEF, for  $t \leq t_{act}$ ). After an abrupt light-mediated increase of concentration  $g_a$  at  $t = t_{act}$  (where  $H(t)$  is the Heaviside function), the time course of GEF concentration for  $t > t_{act}$  follows a decaying exponential.

This input signal consequently triggers a reaction cascade by activating RhoA which in turn activates myosin II. All reactions are modeled by a law of mass action with positive valued activation rate constants  $a$  and  $\tilde{k}$ . Further we assume that all active components deactivate spontaneously described by the positive valued rate constants  $b$  and  $s$  and we express the



**Fig. 3.** Simple model for the RhoA-pathway. (a) Optogenetic activation of strongly adherent cells often results in a homeostatic response, which is described best by a weakly activated linear signaling cascade. For weak perturbations, the strength of the output signal scales linearly with strength of the input signal. (b) Time course of the normalized concentration perturbations of active RhoA (blue) and myosin (red) after rapid increase of GEF concentration (black) upon photoactivation at  $t = t_{act}$ . The dashed line represents a sigmoidal fit to the increasing edge of the myosin concentration in order to estimate the time scale of the increase  $\tau_{\delta\tilde{m}} \approx 11$  s. The inset shows the time evolution of the full system of ODEs in the phase-plane. The green line displays the evolution into the only stable fixed point of the system. Two perturbations for  $\alpha = 2$  (gray) and  $\alpha = 4$  (black) are shown and demonstrate the linearity and scalability of the system.

reaction kinetics as

$$\frac{dR}{dt} = ag(t)(R_T - R) - bR \quad (15)$$

$$\frac{dM}{dt} = \tilde{k}R(M_T - M) - sM \quad (16)$$

where for brevity we write  $R_a \equiv R$  and  $M_a \equiv M$ . Here we additionally assume that the total amount of each signaling component is conserved on the studied time scale, such that concentrations of the inactive species  $R_i$  and  $M_i$  are given by the difference of the total concentration and the active concentration  $R_i = R_T - R$  and  $M_i = M_T - M$ . Another simplification is made by considering the limit of a weakly activated signaling cascade (60) for which  $R_T - R \approx R_T$  and  $M_T - M \approx M_T$  such that the system can be written as

$$\frac{dr}{dt} = ag(t) - br, \quad \frac{dm}{dt} = kr - sm, \quad (17)$$

where we divided by the total concentration and hence set  $r = R/R_T$ ,  $m = M/M_T$  and  $k = \tilde{k}R_T$ . Before photoactivation ( $t \leq t_{act}$ ) we have  $\delta g(t) = 0$  and in this case obtain the steady-state concentrations for RhoA and myosin as

$$r_{ss} = \frac{ag_{ss}}{b}, \quad m_{ss} = \frac{ak}{bs}g_{ss}. \quad (18)$$

The time evolution after perturbation ( $t > t_{act}$ ) may generally be written as

$$r(t) = r_{ss} + \delta r(t), \quad m(t) = m_{ss} + \delta m(t), \quad (19)$$

where  $\delta r(t)$  and  $\delta m(t)$  denote the time-dependent perturbations of the steady state. Together with Eq. (17) we end up with the time evolution of the perturbation which is given by

$$\frac{d\delta r}{dt} = a\delta g(t) - b\delta r, \quad \frac{d\delta m}{dt} = k\delta r - s\delta m. \quad (20)$$

In experiments one usually quantifies the relative activity increase with respect to the activity baseline. We therefore normalize the perturbation with respect to the steady state concentrations and obtain

$$\frac{d\delta \tilde{r}}{dt} = b(\delta \tilde{g}(t) - \delta \tilde{r}), \quad \frac{d\delta \tilde{m}}{dt} = s(\delta \tilde{r} - \delta \tilde{m}), \quad (21)$$

with  $\delta \tilde{g}(t) = \delta g(t)/g_{ss}$ . The strength and time course of the relative RhoA and myosin perturbations is controlled by the two deactivation rates  $b$  and  $s$  as well as the strength of the input signal  $\alpha \equiv g_a/g_{ss}$  and its decay rate  $\lambda$ . For the parametrization of this linearized model we refer the reader to the supplementary text. This system of equations Eq. (21) can be solved analytically for a spatially homogeneous system (solution given in supplemental text). Typical time courses of the perturbations are shown in Fig. 3b, where the inset displays the time evolution of Eq. (17).

## Results

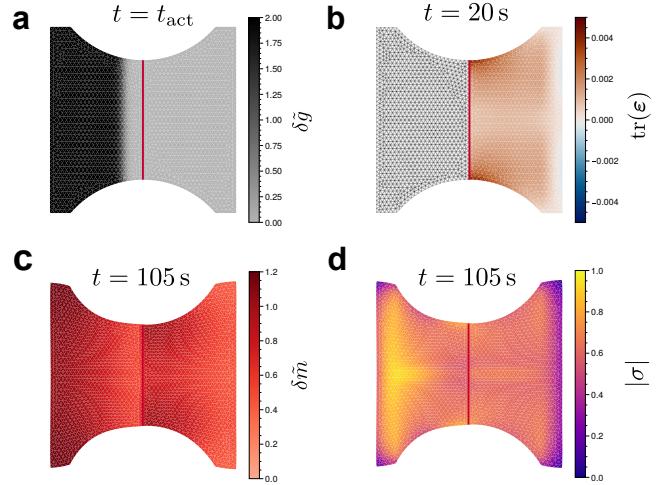
**Optogenetic activation of a cell doublet.** We start by simulating the cell doublet, cf. Fig. 2, with linear Rho-signaling as shown in Fig. 3. The corresponding computer code is documented in the supplemental text and the mechanical equations are parametrized according to Table S3. We keep all parameters fixed, except the strength of the strain-dependent feedback  $a_{\delta \tilde{g}}$  and the viscoelastic time scale  $\tau_c$ . Since we are mainly interested in the response to the perturbation, we omit baseline contractility, i.e. we do not consider a strain in the cell layer before activation. The reference shape was chosen to resemble the typical reference shape of a maturely adherent cell doublet with a vertical oriented cell-cell junction across the symmetry center of the pattern and two pronounced invaginated arcs spanning between the vertical bars of the H-shaped micropattern (49). The cells are assumed to contract isotropically with  $\sigma_a = \sigma_a(\delta \tilde{m})\mathbf{I}$ .

We optogenetically activate the left cell  $\Omega_l$  at time  $t = t_{act}$ , compare Fig. 4a. The time evolution of the GEF-perturbation for  $t \geq t_{act}$  is given by

$$\frac{d\delta \tilde{g}}{dt} = -\lambda \delta \tilde{g} + a_{\delta \tilde{g}} \text{tr}^+(\boldsymbol{\varepsilon}) \mathbf{1}_{\Omega_r}(x), \quad (22)$$

where we include the strain dependent feedback in the right cell via the indicator function  $\mathbf{1}_{\Omega_r}(x)$  with  $\mathbf{1}_{\Omega_r}(x) = 1$  if  $x \in \Omega_r$  and  $\mathbf{1}_{\Omega_r}(x) = 0$  otherwise. This means that the strain-dependent feedback is only active in the right cell  $\Omega_r$ . Having a feedback mechanism in the left cell we can expect non-trivial temporal behavior if positive passive strains build up in the left cell.

The optogenetic activation at  $t_{act} = 5$  s is achieved by setting  $\delta \tilde{g}(t_{act}) = \alpha$ . This time point is shown in Fig. 4a with



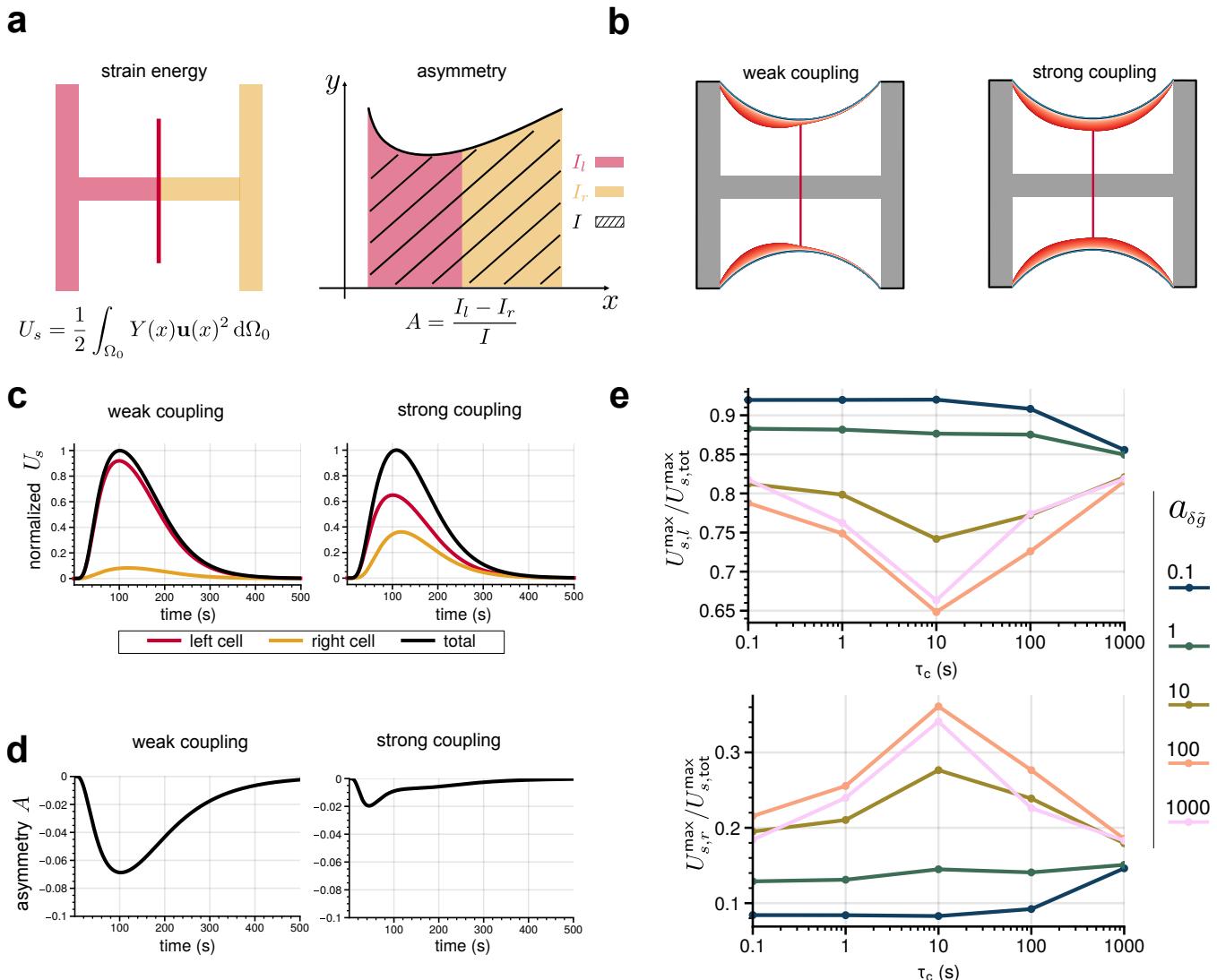
**Fig. 4.** Simulation of the optogenetic activation of a cell doublet. (a) Activated region (in black) and the GEF perturbation  $\delta \tilde{g}(t_{act}) = 2$  at  $t_{act} = 5$  s. In accordance with experiments, only a fraction of the left cell is illuminated in order to avoid illumination of the right cell. (b) Coupling measure  $\text{tr } \boldsymbol{\varepsilon}$  in the non-activated cell (right cell) which reaches its maximal value of approx.  $5 \cdot 10^{-3}$  after 20 s. (c) Myosin concentration  $\delta \tilde{m}$  around the time of maximal strain energy. (d) Frobenius norm of the resulting Cauchy stress. The parameters for this simulation can be found in Tables S2 and S3. Further we used  $a_{\delta \tilde{g}} = 100 \text{ s}^{-1}$ ,  $\tau_c = 10 \text{ s}$ ,  $S = 1$  and time step  $\Delta t = 0.5 \text{ s}$ . Full time sequence as Movie S1. Weak coupling shown as Movie S2.

a 100% increase ( $\alpha = 2$ ) of the steady-state GEF concentration upon photoactivation. This GEF perturbation triggers the RhoA-pathway which leads to active contraction in the activated left cell. As contraction in the left cell progresses, passive positive strains are generated in the right cell as it is stretched (Fig. 4b). This stretch leads to activation of GEF and hence triggers a contractile response in the right cell. Fig. 4c and d show the active myosin in both cells as well as the Frobenius norm of the resulting Cauchy stress  $\|\boldsymbol{\sigma}\|_F = \sqrt{\sum_{i,j=1}^2 |\sigma_{ij}|^2}$ , respectively, for a case where parameters are chosen such that both cells deform approximately symmetrically. We note that the active myosin pattern closely follows the pattern of passive strains in the right cell with concentration peaks near the cell periphery at the cell-cell junction. Looking at the stress pattern, we further notice that the left cell contracts stronger than the right cell. However, the invaginated arc remains fairly symmetrical. This demonstrates that a visually symmetrical contraction can occur even when both cells do not contract equally strongly, but at different locations within the cell. Here the left cell generates active stresses mainly near the vertical bar of the H-pattern, while the right cell generates active stresses more near the periphery.

To investigate these observations further we define different measures in order to understand the input-output relation between the left and right cell and to quantify the efficiency of the coupling. One way to quantify this is to measure the strain-energy  $U_s$  transferred to the substrate

$$U_{s,i} = \frac{1}{2} \int_{\Omega_{0,i}} Y(x) \mathbf{u}^2 d\Omega_{0,i}, \quad i \in \{l, r\} \quad (23)$$

and compare the strain energy deposited on the left and right



**Fig. 5.** Mechanocommunication coupling in cell doublets. (a) One measure for the asymmetry of the process is monitoring the deposited strain energies  $U_s$  in the left and right halves of the micropattern, respectively. Another measure is monitoring shape changes through asymmetry  $A$ , which follows from the integrals under the left and right halves of the contour. (b) Cell shapes in simulations with weak and strong active coupling. Stronger coupling may lead to visually symmetric contraction. Black line represents contour shape at last time step. (c) Effects of weak and strong coupling in terms of strain energy as a function of time. Strain energy curves were normalized with respect to the maximum of the total strain energy curve. (d) Same for shape asymmetry. (e) Efficiency of the coupling defined by the ratio of the relative maxima  $U_{s,l}^{\max}/U_{s,\text{tot}}^{\max}$  for the left vs.  $U_{s,r}^{\max}/U_{s,\text{tot}}^{\max}$  for the right cell, for different combinations of the free parameters, namely coupling strength  $a_{\delta\tilde{g}}$  and viscoelastic time scale  $\tau_c$ . For sufficiently large coupling one sees optimal coupling if the viscoelastic time scale corresponds to the time scale of the linear activation cascade.

parts of the pattern (Fig. 5a (left)). Another way is to measure the asymmetry  $A$  of the contraction by quantifying the shape of the contour  $y(x)$  with respect to the symmetry axis of the pattern and the inward displacement of the cell contour (Fig. 5a (right))

$$A = \frac{I_l - I_r}{I}, \quad (24)$$

with  $I_i = \int_{\Omega_{x,i}} y(x) dx, i \in \{l, r\}$ .

In Fig. 5b we show the shape of the invaginated arc throughout the whole contraction process. This demonstrates that the symmetry of the contraction is strongly shaped by the coupling described by the rate  $a_{\delta\tilde{g}}$ . For a stronger coupling (large value of  $a_{\delta\tilde{g}}$ ) the cell doublet contracts visually symmetrically in comparison to a weaker coupling (small value of  $a_{\delta\tilde{g}}$ ), where invagination of the contour is clearly asymmetric and tends towards the activated cell.

In Fig. 5c we show the normalized strain energy  $U_s$  as a function of time, where each strain energy is normalized with respect to the maximal total strain energy  $U_{s,\text{tot}}$ . We observe that the time course of the total strain energy is only slightly changed by the coupling strength  $a_{\delta\tilde{g}}$ . In the case of weak coupling more than 90% of the deposited strain energy is generated by the left cell and the right cell remains almost completely passive. Note that even for  $a_{\delta\tilde{g}} = 0$  the strain energy on the right hand side of the pattern is expected to be non-zero due to passive deformations by pulling of the left cell. In case of a strong coupling the right cell shows an active response and significantly contributes to the overall generated strain energy. These observations are confirmed by a quantification of the contour deformation as a function of time. For the weak coupling the contour remains strongly asymmetric throughout the majority of the simulation time.

For the strong coupling asymmetry is only present for small times until the right cell actively pulls back and symmetrizes the periphery (Fig. 5d).

Until now we only altered the rate  $a_{\delta\tilde{g}}$  and kept the viscoelastic time scale  $\tau_c$  constant. We next addressed the question of how the viscoelastic properties of the cell influence the efficiency of the coupling and therefore simulated several combinations of  $a_{\delta\tilde{g}}$  and  $\tau_c$  by varying both parameters over several orders of magnitudes. We consider the coupling to be efficient, if the ratio  $U_{r,t}^{\max}/U_{s,tot}^{\max}$  is high. The results are displayed in Fig. 5e.

For both quantifications we find that coupling efficiency is positively correlated with the coupling strength  $a_{\delta\tilde{g}}$ . As a function of the viscoelastic time scale we notice that coupling efficiency increases with an increasing viscoelastic time scale, reaches an optimum around intermediate values and decreases again for larger values of  $\tau_c$ . The optimal value for  $\tau_c$  is found to be at  $\tau_c = 10\text{s}$ , which is in the same order of magnitude as experimentally measured values (48, 61). A sigmoidal fit to the time course of the myosin concentration (Fig. 3b) yields a time scale of  $\tau_{\delta\tilde{m}} \approx 11\text{s}$  similar to the viscoelastic time scale. This result suggests that for an efficient mechanochemical coupling the viscoelastic time scale, i.e. the time scale at which the cell can react to mechanical stimuli, has to be in tune with the time scale at which the full linear cascade can react to those. In case of very large  $\tau_c$  the left cell cannot deform sufficiently to trigger a response in the right cell. For small values of  $\tau_c$  the right cell starts to counteract deformations quickly and does not remain in a stretched state for a sufficiently long time to allow the coupling mechanism to unfold its action.

**Optogenetically stimulated contraction wave in a chain of cells.** Having established a framework for the mechanochemical interplay of two cells, we can generalize to more cells, for example a chain of cells on a micropatterned line (compare Fig. 1b). It is the strength of our discontinuous Galerkin approach that now such simulations are easy to implement and very efficient. The cell chain is realized computationally by connecting equally sized cells along the x-axis. Each cell now adheres in a homogeneous fashion to an elastic substrate. In contrast to the doublet, we here include a mechanochemical coupling also for the activated cell, thus we allow for the possibility that a wave is reflected at the right and comes back to the left. To model that many cell types tend to polarize when placed on lines, we use a unidirectional active stress tensor such that cells only contract in longitudinal direction of the line of cells  $\sigma_a = \sigma_a(\delta\tilde{m})(\mathbf{e}_x \otimes \mathbf{e}_x)$ . All parameters used in the simulation are given in Tables S2 and S4.

We now activate the left cell at  $t = t_{\text{act}}$ . The time evolution of the GEF-concentration for  $t > t_{\text{act}}$  is then described by

$$\frac{d\delta\tilde{g}}{dt} = -\lambda\delta\tilde{g} + a_{\delta\tilde{g}} \text{tr}^+(\boldsymbol{\varepsilon}) . \quad (25)$$

As for the previous study of the cell doublet, we again vary the parameters  $\tau_c$  and  $a_{\delta\tilde{g}}$  to investigate the response of the system. Depending on parameters, we now observe three

different responses: (1) non-transmissive (the stimulus dies out); (2) transmissive wave propagation, i.e. the most right cell is activated once; and (3) oscillatory waves going persistently through the system.

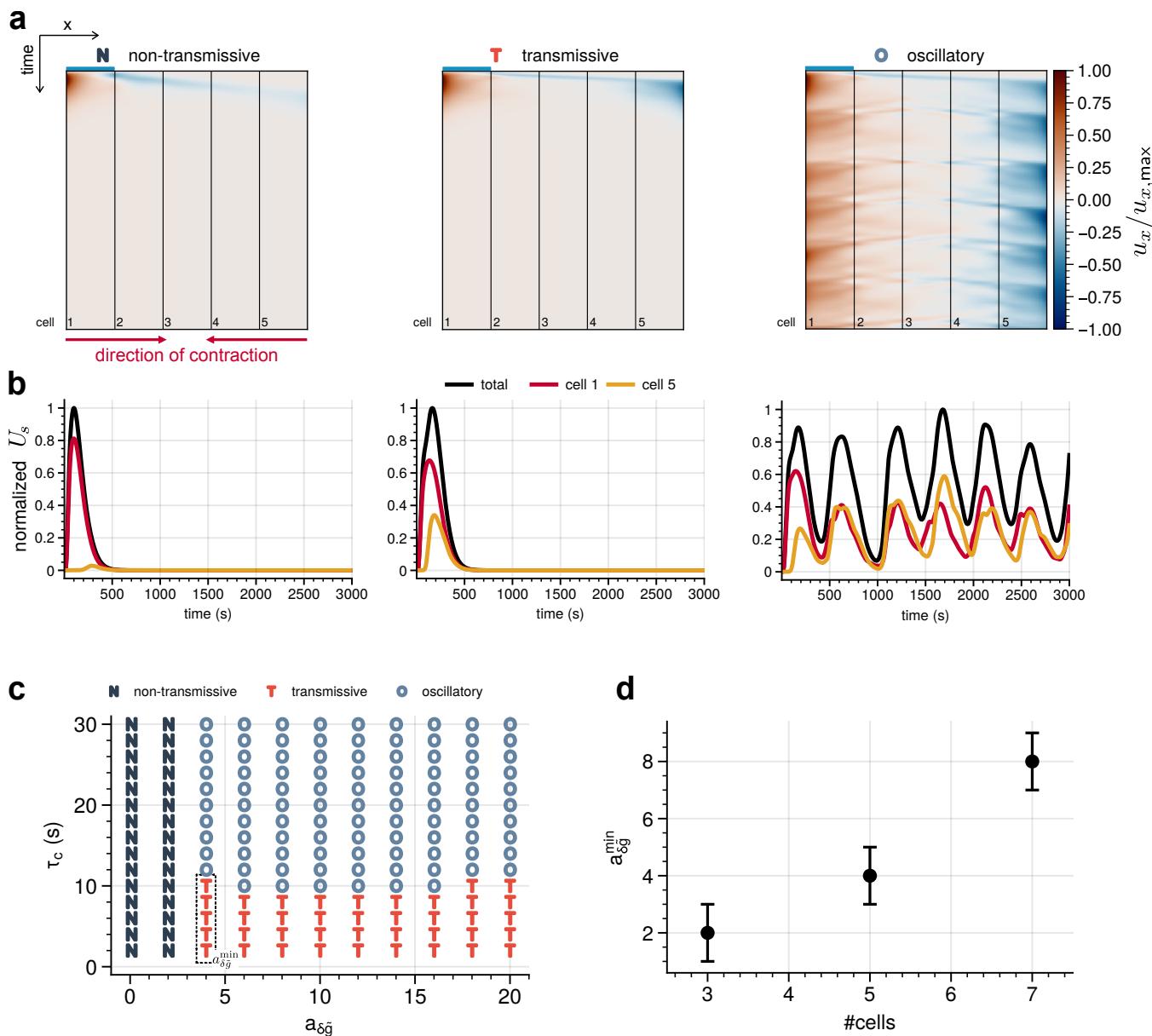
Fig. 6a depicts the displacement field for the different states. Note that the displacement field is directly correlated with the generated traction forces through  $\mathbf{T} = \mathbf{Y}\mathbf{u}$ . In the case of a non-transmissive parameter regime, i.e. for small  $a_{\delta\tilde{g}}$ , the contraction signal strongly decays during propagation from cell 1 (left) to cell 5 (right) and no substantial traction forces are generated at the right end of the line of cells, see Fig. 6a on the left. This observation has been quantified by comparing the substrate strain energies generated by cell 1 and 5 as a function of time, see Fig. 6b on the left.

With increasing values of  $a_{\delta\tilde{g}}$ , the transmission of the signal becomes more and more efficient and the active response of cell 5 comparable to cell 1, see the middle panels of Fig. 6a and b. Whether the signal transmission is effective or not depends on the context; here we decided to call the system transmissive if  $U_s^{\max,5} > 0.1U_s^{\max,1}$ .

Finally, varying also the viscoelastic time scale of the system, we observe persistent oscillatory states in the parameter regime of sufficiently large  $a_{\delta\tilde{g}}$  and  $\tau_c$ , see the right panels of Fig. 6a and b. The frequency of the oscillations depends strongly on the combination of  $a_{\delta\tilde{g}}$  and  $\tau_c$  and can be further classified into burst-like oscillations and contractile oscillations. The former correspond to large variations in strain energy, while the latter relate to small fluctuations around an elevated increased strain energy plateau (see Fig. S2).

Fig. 6c shows the phase diagram as a function of the coupling strength and the viscoelastic time scale. For a strongly coupled system (i.e. sufficiently large  $a_{\delta\tilde{g}}$ ), the transition between transmissive and oscillatory states occurs around  $\tau_c \approx 10\text{s}$ , which again coincides with the time scale of the myosin relaxation. The number of cells in the line is also relevant for the signal transmission. Fig. 6d shows that the transition from non-transmissive to transmissive mechanochemical signaling needs larger values of  $a_{\delta\tilde{g}}$  when increasing the length of the cell chain. This emphasizes that mechanochemical signaling tends to be of dissipative nature, and hence a cell can reach out only to a limited number of other cells, except if a strong amplification exists, like in action potentials.

**Cell monolayer with non-linear Rho-pathway.** We finally turn to a cell monolayer (compare Fig. 1b). Again the numerical implementation is relatively easy given our discontinuous Galerkin approach and we demonstrate this here for 28 hexagonally arranged cells. In contrast to the cell doublet on a H-pattern and the line of cells, we now cannot assume anymore that the cells in the layer are polarized. This also implies that the simple linear chain model for the Rho-pathway might not be sufficient anymore and that more complex dynamics might arise. We therefore now use the full non-linear model for the Rho-pathway as established earlier by Kamps et al. (32). The corresponding kinetic equations are given in Eqs. (S29-S31) (supplemental text). As investigated in Kamps et al. (32), they exhibit Turing-type instabilities resulting from fast (inactive) and slow (active) diffusing



**Fig. 6.** Mechanocommunication in a chain of cells. (a) Kymographs of the substrate displacement field normalized to the maximal displacement for five cells in a row and for three different conditions. At  $t = 5$  s cell 1 (left) is activated (blue bar). The contraction of the activated cell initiates a contraction wave propagating from cell 1 to cell 5 (right). Depending on the parameters we observe non-transmissive (N), transmissive (T) or oscillatory states (O). For sufficiently large strain-dependent feedback  $a_{\delta g}$  and sufficiently large viscoelastic time scale  $\tau_c$ , self-sustained oscillations emerge. (b) Time evolution of the strain energy for the activated cell 1 and cell 5, i.e. the last cell of the line, corresponding to the kymographs given in (a). (c) Phase diagram as a function of activation strength and viscoelastic timescale. Strong coupling and large viscoelastic times are required for oscillations. (d) Effect of cell number. The transition from non-transmissive to transmissive occurs at larger values of  $a_{\delta g}$  with increasing length of the cell chain (error bars highlight discrete parameter sampling). A full simulation is given as Movie S3.

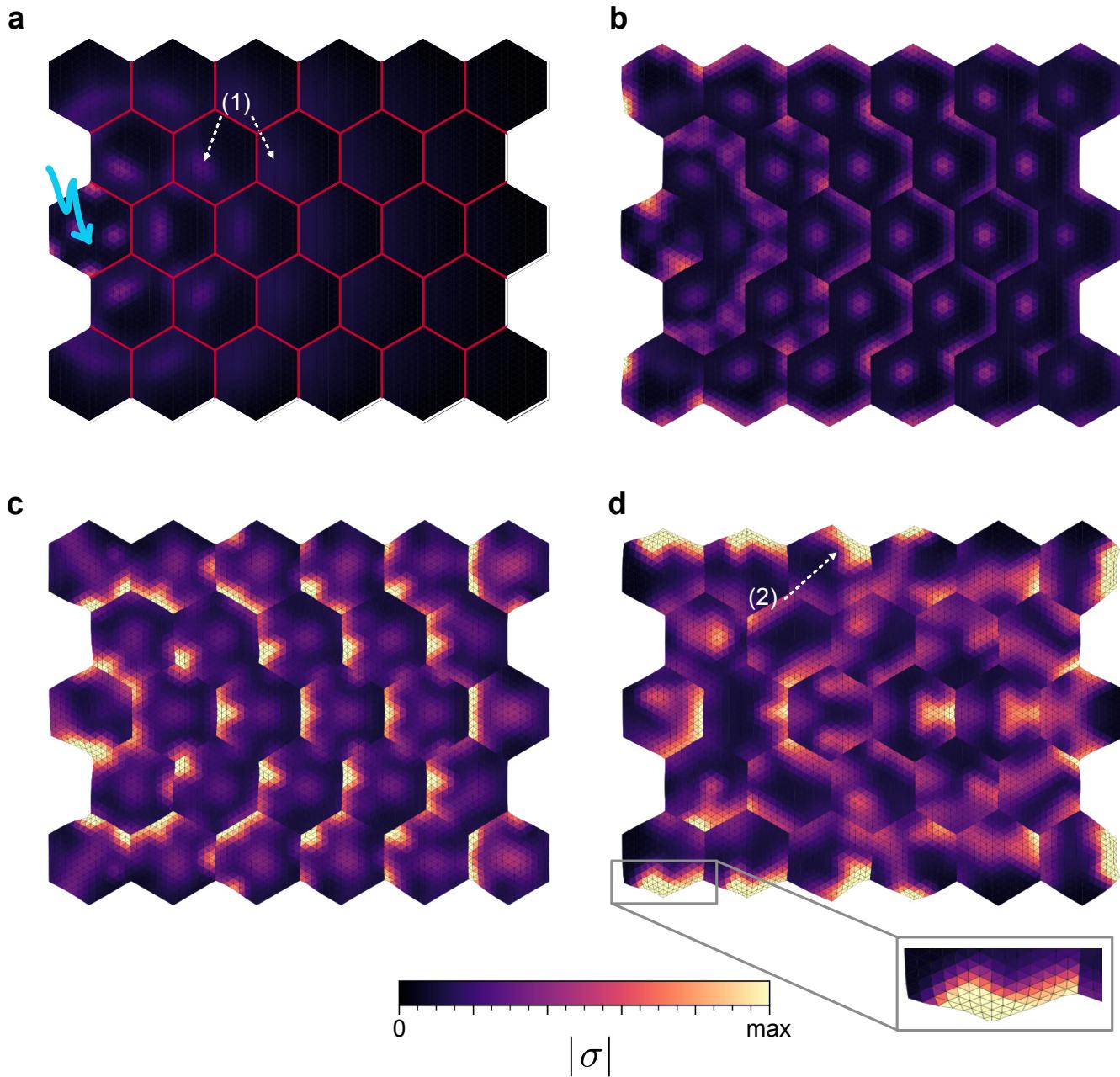
species paired with positive and negative feedback loops of activator-inhibitor type. Here we have chosen the parameters for the RD-system such that traveling waves can form.

The cell monolayer is shown in Fig. 7a with intercellular junctions shown in red and the color code depicting the levels of active stress/active myosin. The cell in the middle on the left hand side of the monolayer was activated by inducing an instability through small random fluctuations in the GEF- and RhoA-concentrations (the same effect can be obtained by optogenetic activation, but for the non-linear model, the exact mode of activation is less relevant). Several distinct contraction peaks form and the induced deformations slowly activate the RhoA-pathway and allow the active stresses to

spread through the tissue, as indicated by the white arrows in Fig. 7a. The initially weak and rather uniform contractions eventually turn into strong and more localized traveling contraction waves, see Fig. 7b, until the whole monolayer is strongly activated, see Fig. 7c. For longer times, a dynamic steady state is reached, where the deformations are most prominent near the free edges, see Fig. 7d.

## Discussion and Conclusion

Here we have shown that the discontinuous Galerkin (DG) finite element method (FEM) is ideally suited to model mechanochemical coupling in cell layers. Because both the



**Fig. 7.** Mechanocomplex coupling in a cell monolayer with a non-linear model for the Rho-pathway. (a) Total stress in the tissue shortly after inducing a spatio-temporal contraction pattern in the centered cell on the left side of the tissue. This initial perturbation spreads by means of the mechanochemical feedback through the tissue (white arrows). (b) and (c) Tissue at a later stage, where the initially small perturbations have developed into substantial contraction waves in each of the cells. (d) After transient dynamics, prominent deformations are visible in the free edges of the cell layer (white arrow and inset). Parameters can be found in Table S1 and Table S5. Full dynamics shown as Movie S4.

reaction-diffusion (RD) and the continuum mechanical models lead to partial differential equations (PDEs), finite elements are the natural approach to couple them in a numerically efficient framework. The DG method in addition is ideal to include cell boundaries while still keeping the continuous nature of the PDEs. Our approach is very general both in terms of biochemistry (as exemplified by the linear regulation cascade versus the fully nonlinear reaction-diffusion system) and the material law (here a linear Kelvin-Voigt-type material). Motivated by the homeostatic nature of adherent cell layers, it is however centered on elastic systems. For flowing systems, which are typically modeled with active gel

theory (22–26), one had to switch from the Lagrangian to the Eulerian framework.

We benchmarked our approach by investigating in detail the optogenetic activation of a cell doublet on a H-shaped micropattern, as recently studied experimentally in Ref. (49). We then exemplified the scalability by looking at force and signal transmission via contraction waves in chains of cells, similar to recent experiments on optogenetic activation of cell trains (50). In these two cases, cell-matrix adhesion is very strong and cells tend to be homeostatic, which means that they return to baseline after optogenetic stimulation (48). Therefore we used the simple model of a linear chain for

the Rho-signaling pathway. We finally addressed the case of mechanochemically excitable monolayers, which are known to develop more complex dynamic patterns, possibly because cell-cell adhesion dominates and cells are less polarized. In particular, experiments have found that wave propagation is rather common in such systems (7, 9, 10). In this case, we therefore used a more comprehensive and non-linear model for the Rho-pathway (32).

In all of these cases, we identified conditions under which mechanochemical signaling leads to strong propagation of the signal from one cell to the other, and even to wave propagation. We find that force transmission is best when the viscoelastic time scale of the cell and the time scale of relaxation of the Rho-pathway after activation are of the same order. For the cell doublet, we used the coupling to an elastic foundation as a readout of the mechanical coupling of the two neighboring cells, in addition to the asymmetry in shape. In the future, the coupling to the elastic foundation could be replaced by a continuum substrate; then one could also model the effect of mechanical cell-cell communication through the substrate, which would be a natural extension of our approach. On the biochemical side, it would be interesting to go beyond modelling of the Rho-pathway and also include the effect of other known signaling molecules, including Rac/Cdc42, ERK and merlin. The numerical DG FEM framework established here now opens the door to quickly explore the effect of such pathways, and thus to establish a multiscale modeling framework that connects molecular processes to effective systems behavior.

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## Author Contributions

All authors designed the research together. D.W. performed the research. F.Z. and U.S.S. supervised the project. D.W. and U.S.S. wrote the original draft of the paper. All authors reviewed and approved the paper.

## Declaration of interests

The authors declare no competing interests.

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# Modelling mechanochemical coupling in optogenetically activated cell layers

## - Supplemental text -

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### General notation

In solid mechanics one typically expresses model equations in the Lagrangian (material) framework by describing a deforming solid in terms of coordinates  $\hat{\mathbf{x}}$  representing the position of material particles in the undeformed configuration  $\Omega_0$ . The current position of the material particles in the deformed configuration  $\Omega(t)$  at time  $t$  are given by  $\mathbf{x} = \chi(\hat{\mathbf{x}}, t)$ . The two configurations are connected by the displacement vector field  $\hat{\mathbf{u}}(\hat{\mathbf{x}}, t) = \mathbf{x}(\hat{\mathbf{x}}, t) - \hat{\mathbf{x}}$ . The deformation gradient tensor is defined as  $\hat{\mathbf{F}} = \partial \mathbf{x} / \partial \hat{\mathbf{x}} = \mathbf{I} + \hat{\nabla} \hat{\mathbf{u}}$  and measures the local change of relative position of two points at the transition from the undeformed to the deformed configuration. Its determinant  $\hat{J} = \det(\hat{\mathbf{F}})$  represents the local volume change. Describing the governing equations in terms of the coordinates  $\mathbf{x}$  is known as the Eulerian framework where a fixed point in space is observed. In the limit of linear elasticity we do not distinguish between Lagrangian and Eulerian description and drop the  $\wedge$ -symbol.

### Reaction-diffusion on time dependent domains in Lagrangian frame of reference

For the pull-back of

$$\frac{\partial c_i}{\partial t} + \nabla \cdot (\mathbf{v}(\mathbf{x}, t) c_i) = \nabla \cdot (\mathbf{D} \nabla c_i) + R_{c_i}(t) \quad (\text{S1})$$

to the reference configuration (Lagrangian coordinates) we exploit the transformation rules for scalar and vector fields as well as the involved differential operators (1). For mappings between the two reference systems we use the motion function  $\mathbf{x} = \chi(\hat{\mathbf{x}}, t)$ . Each Eulerian field has a Lagrangian counterpart which states the equivalence of the two descriptions. Hence we write  $c(\mathbf{x}, t) = \hat{c}(\hat{\mathbf{x}}, t)$  for the concentration field and  $\mathbf{v}(\mathbf{x}, t) = \hat{\mathbf{v}}(\hat{\mathbf{x}}, t)$  for the velocity field. Here  $\hat{\mathbf{v}} = \partial_t \chi(\hat{\mathbf{x}}, t)$  denotes the material velocity. For the gradient of the scalar field  $c(\mathbf{x}, t)$  it holds

$$\nabla c = \hat{\mathbf{F}}^{-\top} \hat{\nabla} \hat{c}. \quad (\text{S2})$$

For the gradient of the vector field  $\mathbf{v}$  we have

$$\nabla \mathbf{v} = \hat{\nabla} \hat{\mathbf{v}} \hat{\mathbf{F}}^{-1}. \quad (\text{S3})$$

The divergence of the vector field transforms according to

$$\nabla \cdot \mathbf{v} = \frac{1}{\hat{J}} \hat{\nabla} \cdot (\hat{J} \hat{\mathbf{F}}^{-1} \hat{\mathbf{v}}), \quad (\text{S4})$$

and we note that Piola's identity is given by

$$\hat{\nabla} \cdot (\hat{J} \hat{\mathbf{F}}^{-1}) = 0. \quad (\text{S5})$$

The material time derivative of a field expressed in Eulerian coordinates is given by the convective derivative

$$\frac{d}{dt} c(\mathbf{x}, t) = \frac{\partial}{\partial t} c + \mathbf{v} \cdot \nabla c \equiv \frac{\partial \hat{c}}{\partial t} \quad (\text{S6})$$

Starting from the reaction-diffusion equation in Eulerian coordinates

$$\frac{\partial c_i}{\partial t} + \mathbf{v} \cdot \nabla c_i + c_i (\nabla \cdot \mathbf{v}) = \nabla \cdot (\mathbf{D} \nabla c_i) + R_{c_i}(t), \quad (\text{S7})$$

we note that the first two terms correspond to the convective time derivative. The third term on the left and the first term on the right hand side of the equation can be replaced by using the Piola transform Eq. (S4) such that

$$\frac{\partial \hat{c}_i}{\partial t} + \hat{c}_i \frac{1}{\hat{J}} \hat{\nabla} \cdot (\hat{J} \hat{\mathbf{F}}^{-1} \hat{\mathbf{v}}) = \frac{1}{\hat{J}} \hat{\nabla} \cdot (\hat{J} \hat{\mathbf{F}}^{-1} \mathbf{D} \hat{\mathbf{F}}^{-\top} \hat{\nabla} \hat{c}_i) + R_{\hat{c}_i}(t), \quad (\text{S8})$$

and after multiplying by  $\hat{J}$  we obtain

$$\hat{J} \frac{\partial \hat{c}_i}{\partial t} + \hat{c}_i \hat{\nabla} \cdot (\hat{J} \hat{\mathbf{F}}^{-1} \hat{\mathbf{v}}) = \hat{\nabla} \cdot (\hat{J} \hat{\mathbf{F}}^{-1} \mathbf{D} \hat{\mathbf{F}}^{-\top} \hat{\nabla} \hat{c}_i) + \hat{J} R_{\hat{c}_i}(t). \quad (\text{S9})$$

Applying Piola's identity to the second term on the left we find

$$\hat{c}_i \hat{\nabla} \cdot (\hat{J} \hat{\mathbf{F}}^{-1} \hat{\mathbf{v}}) = \hat{c}_i \hat{J} \hat{\mathbf{F}}^{-1} \hat{\nabla} \hat{\mathbf{v}} = \hat{c}_i \hat{J} \hat{\mathbf{F}}^{-1} \frac{\partial \hat{\mathbf{F}}}{\partial t} = \hat{c}_i \frac{\partial \det(\hat{\mathbf{F}})}{\partial t} = \hat{c}_i \frac{\partial \hat{J}}{\partial t}, \quad (\text{S10})$$

and further using  $\hat{\mathbf{C}} = \hat{\mathbf{F}}^\top \hat{\mathbf{F}}$  we end up with

$$\frac{\partial}{\partial t} (\hat{J} \hat{c}_i) = \hat{\nabla} \cdot (\hat{J} \mathbf{D} \hat{\mathbf{C}}^{-1} \hat{\nabla} \hat{c}_i) + \hat{J} R_{\hat{c}_i}(t). \quad (\text{S11})$$

## Finite-Element formulation

### Symmetric Weighted Interior Penalty Discontinuous Galerkin method

The interface condition on the cell-cell junction

$$-\hat{J} \mathbf{D} \hat{\mathbf{C}}^{-1} \hat{\nabla} \hat{c}_i \cdot \mathbf{N}_{\text{CCJ}} = 0 \quad \text{on } \Gamma_{\text{CCJ}}, \quad (\text{S12})$$

leads to a discontinuity in the solution. In order to account for abrupt concentration changes from one subdomain to the other we need a method which allows discontinuous functions across the membrane. The standard choice for such a problem is the discontinuous Galerkin method. In contrast to the continuous Galerkin methods, continuity and smoothness of the involved DG-functions is only enforced element-wise such that the solution may be discontinuous across element boundaries. If and where desired, continuity can be enforced through an appropriate penalty term. These methods are known as interior penalty discontinuous Galerkin methods (IPDG) (2–4). However, as can be seen from Eq. (S11) the diffusivity  $\boldsymbol{\alpha} \equiv \hat{J}\mathbf{D}\hat{\mathbf{C}}^{-1}$  in the Lagrangian frame is position dependent due to local deformations of the domain. Hence, we are dealing with heterogeneous diffusion and use a Symmetric Weighted Interior Penalty (SWIP) discontinuous Galerkin scheme (5). Let  $\mathcal{T}(\Omega_0)$  be the triangulation of the domain  $\Omega$  into finite elements  $e \in \mathcal{T}(\Omega_0)$ . Further, let  $\mathcal{F}$  denote the union of the boundary facets of all elements  $e$ . We distinguish between external facets  $\mathcal{F}_{\text{ext}}$ , internal facets  $\mathcal{F}_{\text{int}}$  and membrane facets  $\mathcal{F}_M$  such that  $\mathcal{F} = \mathcal{F}_{\text{ext}} \cup \mathcal{F}_{\text{int}} \cup \mathcal{F}_M$  with  $\mathcal{F}_{\text{int}} = \mathcal{F} \setminus (\mathcal{F}_{\text{ext}} \cup \mathcal{F}_M)$ . Next, by  $\hat{c}_-$  and  $\hat{c}_+$  we denote scalar valued functions on two neighboring elements  $e_-$  and  $e_+$ . The normal vectors on a common facet of  $e_{\pm}$  are given by  $\mathbf{N}_{\pm}$ . For example,  $\mathbf{N}_-$  defines the outward directed normal on  $e_-$  pointing into  $e_+$ . Following the SWIP-DG notations we introduce the jump and the weighted average of a quantity as  $[\hat{c}] \equiv \hat{c}_+ \mathbf{N}_+ + \hat{c}_- \mathbf{N}_-$  and  $\{\hat{c}\}_{\omega} \equiv \omega_+ \hat{c}_+ + \omega_- \hat{c}_-$ , respectively. Analogously, for piecewise vector valued functions  $\hat{\mathbf{q}}$  one defines jump and weighted average as  $[\hat{\mathbf{q}}] \equiv \hat{\mathbf{q}}_+ \mathbf{N}_+ + \hat{\mathbf{q}}_- \mathbf{N}_-$  and  $\{\hat{\mathbf{q}}\}_{\omega} \equiv \omega_+ \hat{\mathbf{q}}_+ + \omega_- \hat{\mathbf{q}}_-$ , respectively. The weights are defined as  $\omega_{\pm} = \delta_{\alpha}^{\mp}/(\delta_{\alpha}^+ + \delta_{\alpha}^-)$ , where  $\delta_{\alpha}^{\mp}$  is obtained from the diffusivity on two neighbouring elements  $e_{\mp}$  by calculating  $\delta_{\alpha}^{\mp} = \tilde{\mathbf{N}}_e^T \boldsymbol{\alpha}_{\mp} \tilde{\mathbf{N}}_e$ . Note that the weights fulfill  $\omega_+ + \omega_- = 1$ . Since we are only interested in having a discontinuity across the membrane facets  $\mathcal{F}_M$  we introduce a diffusion dependent penalty term to penalize jumps across all other internal facets  $\mathcal{F}_{\text{int}}$  which is defined as the harmonic mean  $\gamma_{\alpha} = 2\delta_{\alpha}^+ \delta_{\alpha}^- / (\delta_{\alpha}^+ + \delta_{\alpha}^-)$ . Moreover, one may use these definitions to prove the identity

$$[\hat{\mathbf{q}}\hat{c}] = [\hat{\mathbf{q}}]\{\hat{c}\}_{\omega} + \{\hat{\mathbf{q}}\}_{\omega}[\hat{c}] . \quad (\text{S13})$$

In the first step of the derivation of the DG weak form we multiply Eq. (S11) with a suitable test function  $v_c \in \mathcal{V}$  and integrate over the whole simulation domain  $\Omega_0$  which gives

$$\begin{aligned} & \int_{\Omega_0} \frac{\partial}{\partial t} (\hat{J}\hat{c}) v_c \, d\Omega_0 - \int_{\Omega_0} \hat{\nabla} \cdot (\boldsymbol{\alpha} \hat{\nabla} \hat{c}) v_c \, d\Omega_0 \\ & \quad - \int_{\Omega_0} \hat{J} R_c(t) v_c \, d\Omega_0 = 0 . \end{aligned} \quad (\text{S14})$$

Instead of directly using partial integration on the middle term of Eq. (S14) we first split it into a sum over element integrals and then apply Green's first theorem to obtain

$$\begin{aligned} \int_{\Omega_0} \hat{\nabla} \cdot (\boldsymbol{\alpha} \hat{\nabla} \hat{c}) v_c \, d\Omega_0 &= \sum_{e \in \mathcal{T}(\Omega_0)} \int_e \hat{\nabla} \cdot (\boldsymbol{\alpha} \hat{\nabla} \hat{c}) v_c \, d\Omega_0 \\ &= \sum_{f_e \in \mathcal{F}(\Omega_0)} \int_{f_e} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \tilde{\mathbf{N}}_e v_c \, ds \\ &\quad - \sum_{e \in \mathcal{T}(\Omega_0)} \int_e \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \hat{\nabla} v_c \, d\Omega_0 . \end{aligned} \quad (\text{S15})$$

Here,  $f_e$  denotes the facets of element  $e$  and  $\tilde{\mathbf{N}}_e$  describes the outward directed normal vector on the facets of the element. The first term in Eq. (S15) is split again into the exterior, interior and membrane facets

$$\begin{aligned} \sum_{f_e \in \mathcal{F}(\Omega_0)} \int_{f_e} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \tilde{\mathbf{N}}_e v_c \, ds &= \sum_{f_e \in \mathcal{F}_{\text{ext}}(\Omega_0)} \int_{f_e} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \tilde{\mathbf{N}}_e v_c \, ds + \sum_{f_e \in \mathcal{F}_{\text{int}}(\Omega_0)} \int_{f_e} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \tilde{\mathbf{N}}_e v_c \, ds \\ &\quad + \sum_{f_e \in \mathcal{F}_{\mathcal{M}}(\Omega_0)} \int_{f_e} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \tilde{\mathbf{N}}_e v_c \, ds . \end{aligned} \quad (\text{S16})$$

Note that each internal facet and each membrane facet is shared by two adjacent elements  $e_-$  and  $e_+$  (see Fig. S1) such that integrals along the common facets add up to a jump

$$\int_{f_{\pm}} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \tilde{\mathbf{N}}_{\pm} v_c \, ds = \int_f (\delta_{\alpha}^+ \hat{\nabla} \hat{c}_+ v_{c,+} - \delta_{\alpha}^- \hat{\nabla} \hat{c}_- v_{c,-}) \cdot \tilde{\mathbf{N}}_+ \, ds = \int_f [\![\boldsymbol{\alpha} \hat{\nabla} \hat{c} v_c]\!] \, ds . \quad (\text{S17})$$

Summing up over all elements  $e$  in Eq. (S15) and Eq. (S16) while respecting zero-flux boundary conditions yields

$$\int_{\Omega_0} \hat{\nabla} \cdot (\boldsymbol{\alpha} \hat{\nabla} \hat{c}) v_c \, d\Omega_0 = - \int_{\Omega_0} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \hat{\nabla} v_c \, d\Omega_0 + \int_{\mathcal{F}_{\text{int}}} [\![\boldsymbol{\alpha} \hat{\nabla} \hat{c} v_c]\!] \, ds . \quad (\text{S18})$$

The last term in Eq. (S18) is further expanded using the identity in Eq. (S13) which yields

$$\int_{\mathcal{F}_{\text{int}}} [\![\boldsymbol{\alpha} \hat{\nabla} \hat{c} v_c]\!] \, ds = \int_{\mathcal{F}_{\text{int}}} [\![\boldsymbol{\alpha} \hat{\nabla} \hat{c}]\!] \cdot \{v_c\}_{\omega} \, ds + \int_{\mathcal{F}_{\text{int}}} \{\boldsymbol{\alpha} \hat{\nabla} \hat{c}\}_{\omega} \cdot [\![v_c]\!] \, ds . \quad (\text{S19})$$

Since the exact solution of the diffusion equation is expected to be smooth we enforce continuity of the fluxes by setting  $[\![\boldsymbol{\alpha} \hat{\nabla} \hat{c}]\!] = 0$ . To further enforce continuity of the solution we exploit  $[\![\hat{c}]\!] = 0$  and add a term to symmetrize the problem. Additionally, we ensure stability of the problem by adding a stabilizing term according to Ern et al. (5) and Douglas and Dupont (6) which finally leads to

$$\int_{\mathcal{F}_{\text{int}}} [\![\boldsymbol{\alpha} \hat{\nabla} \hat{c} v_c]\!] \, ds = \int_{\mathcal{F}_{\text{int}}} \{\boldsymbol{\alpha} \hat{\nabla} \hat{c}\}_{\omega} \cdot [\![v_c]\!] \, ds + \int_{\mathcal{F}_{\text{int}}} \{\boldsymbol{\alpha} \hat{\nabla} v_c\}_{\omega} \cdot [\![\hat{c}]\!] \, ds - \int_{\mathcal{F}_{\text{int}}} \frac{s_N}{h} \gamma_{\alpha} [\![\hat{c}]\!] \cdot [\![v_c]\!] \, ds . \quad (\text{S20})$$

In Eq. (S20),  $s_N$  denotes the so-called Nitsche parameter, which must be chosen sufficiently large to ensure continuity across internal facets (7), and  $h$  the average element diameter. Next, we define

$$\begin{aligned} \mathcal{D}(\hat{c}, v_c, \boldsymbol{\alpha}) &:= \int_{\Omega_0} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \hat{\nabla} v_c \, d\Omega_0 - \int_{\mathcal{F}_{\text{int}}} \{\boldsymbol{\alpha} \hat{\nabla} \hat{c}\}_{\omega} \cdot [\![v_c]\!] \, ds \\ &\quad - \int_{\mathcal{F}_{\text{int}}} \{\boldsymbol{\alpha} \hat{\nabla} v_c\}_{\omega} \cdot [\![\hat{c}]\!] \, ds + \int_{\mathcal{F}_{\text{int}}} \frac{s_N}{h} \gamma_{\alpha} [\![\hat{c}]\!] \cdot [\![v_c]\!] \, ds , \end{aligned} \quad (\text{S21})$$

and hence arrive at the final weak form statement of Eq. (S11) which reads

$$\int_{\Omega_0} \frac{\partial}{\partial t} (\hat{J} \hat{c}) v_c \, d\Omega_0 + \mathcal{D}(\hat{c}, v_c, \boldsymbol{\alpha}) - \int_{\Omega_0} \hat{J} R_c(t) v_c \, d\Omega_0 = 0 . \quad (\text{S22})$$

We note that an integral part of our model design is that continuity is only enforced on the internal edges. Thus jumps are possible only across the interface of the two subdomains i.e. across the membrane. In our case this means that the reactants in each cell cannot pass the cell-cell junction. This leads to a variety of possibilities in the treatment of multicellular systems. Cellular contractility in principle can be described by distinct reaction-diffusion systems in each cell. The RD-systems within the cells can then be coupled by appropriate mechano-chemical coupling terms to account for mechanosensing at the intercellular junction.

The weak form of Eq. (S11) finally reads

$$0 = \int_{\Omega_0} \frac{\partial}{\partial t} (\hat{J}\hat{c})v_c \, d\Omega_0 + \int_{\Omega_0} \boldsymbol{\alpha} \hat{\nabla} \hat{c} \cdot \hat{\nabla} v_c \, d\Omega_0 \\ - \underbrace{\int_{\mathcal{F}_{\text{int}}} \{\boldsymbol{\alpha} \hat{\nabla} \hat{c}\}_\omega \cdot [\![v_c]\!] \, ds}_{\text{consistency}} - \underbrace{\int_{\mathcal{F}_{\text{int}}} \{\boldsymbol{\alpha} \hat{\nabla} v_c\}_\omega \cdot [\![\hat{c}]\!] \, ds}_{\text{symmetry}} + \underbrace{\int_{\mathcal{F}_{\text{int}}} \frac{s_N}{h} \gamma_\alpha [\![\hat{c}]\!] \cdot [\![v_c]\!] \, ds}_{\text{penalty}} - \int_{\Omega_0} \hat{J}R_c(t)v_c \, d\Omega_0,$$

where  $s_N$  denotes the Nitsche parameter, which must be chosen sufficiently large to ensure continuity across internal facets (7), and  $h$  the average element diameter. The notation is illustrated in Fig. S1a.

## Weak formulation for the elastic domain

To derive the weak formulation of

$$\nabla \cdot \boldsymbol{\sigma} = Y(\mathbf{x})\mathbf{u}, \quad (\text{S23})$$

we multiply with a vector valued test function  $\mathbf{v} \in \mathbf{V}(\Omega_0)$  and integrate over the domain  $\Omega_0$  of the undeformed configuration

$$\int_{\Omega_0} (\nabla \cdot \boldsymbol{\sigma}) \cdot \mathbf{v} \, d\Omega_0 = \int_{\Omega_0} Y(\mathbf{x})\mathbf{u}(\mathbf{x}) \cdot \mathbf{v} \, d\Omega_0. \quad (\text{S24})$$

The left hand side can be integrated using integration by parts i.e. using the following identity

$$\nabla \cdot (\boldsymbol{\sigma} \cdot \mathbf{v}) = (\nabla \cdot \boldsymbol{\sigma}) \cdot \mathbf{v} + \boldsymbol{\sigma} : \nabla \mathbf{v}. \quad (\text{S25})$$

This allows to simplify Eq. (S24) to

$$\int_{\Omega_0} \boldsymbol{\sigma} : \nabla \mathbf{v} \, d\Omega_0 - \int_{\Gamma} (\boldsymbol{\sigma} \cdot \mathbf{N}) \cdot \mathbf{v} \, ds + \int_{\Omega_0} Y\mathbf{u} \cdot \mathbf{v} \, d\Omega_0 = 0. \quad (\text{S26})$$

Here,  $\boldsymbol{\sigma} \cdot \mathbf{N}$  is the traction vector at the boundary  $\Gamma = \partial\Omega_0$  which is set to zero in case of stress free boundaries and hence, the final weak form statement reads

$$\int_{\Omega_0} \boldsymbol{\sigma} : \nabla \mathbf{v} \, d\Omega_0 + \int_{\Omega_0} Y\mathbf{u} \cdot \mathbf{v} \, d\Omega_0 = 0. \quad (\text{S27})$$

## Time-discretisation

All time dependent quantities  $Q(t)$  are discretized using an implicit (backward Euler) scheme at a given time  $t^{(n+1)}$

$$\left(\frac{dQ}{dt}\right)^{(n+1)} \approx \frac{Q^{(n+1)} - Q^{(n)}}{\Delta t}. \quad (\text{S28})$$

## Mesh generation

The meshes for the three different systems were generated with Gmsh (9). For the cell chain and the tissue-like monolayer we made sure to create a mesh which respects the symmetry of the system. The meshes are shown in Fig. S1c.

## Literature review RhoA-pathway

Having reviewed the relevant literature, we found that the model as presented by Kamps et al. (8) contains all important components which are necessary for a profound description of the RhoA pathway. In contrast to the RhoA-actomyosin system as introduced by Staddon et al. (10) it explicitly contains GEF as a downstream effector of RhoA, and thus provides an important interface for light-induced contraction as GEF activity can be controlled by optogenetic constructs like the CRY2/CIBN system. In combination with experimental measurements Kamps et al. (8) proposed a reaction scheme for the active reactants GEF (G), RhoA (R) and myosin (M) which reads

$$\frac{dG}{dt} = k_3R(G_T - G) - k_4GM \quad (\text{S29})$$

$$\frac{dR}{dt} = \frac{k_1G(R_T - R)}{K_{m1} + R_T - R} - k_2\frac{R}{K_{m2} + R} \quad (\text{S30})$$

$$\frac{dM}{dt} = \frac{k_5R(M_T - M)}{K_{m5} + M_T - M} - k_6\frac{M}{K_{m6} + M}. \quad (\text{S31})$$

$G_T$ ,  $R_T$  and  $M_T$  denote the total concentrations of the species which the authors assume to be constant. The rate constants are denoted by  $k_i$  and the Michaelis-Menten constants are given by the  $K_{mi}$ .

The membrane and cytosol associated species represent the active and passive states, respectively. This terminology stems from experimental studies which show that the active forms of RhoA and myosin are predominantly found in the vicinity of the plasma membrane and the submembraneous actin cortex. In contrast, the inactive forms are associated with the cytosol (11, 12). The RhoA protein for example exhibits a lipophilic end which enables it to bind to lipid membranes (13). However, so-called guanosine dissociation inhibitors (GDIs) may bind to Rho-GDPs, not only keeping them in a permanently inactive state but also preventing its membrane localization by shielding the hydrophilic end and additionally making it soluble in the cytoplasm (14). The reaction scheme also highlights the two feedback loops which are important to describe the excitable and oscillatory dynamics that are

observed in experiments (see Fig. S1 d). The positive feedback loop stems from the observation that RhoA activity at the membrane further induces GEF membrane recruitment. Due to Rho activation by GEFs, this closes a positive feedback loop (8). The negative feedback loop can be traced back to the ability of myosin to inhibit the nucleotide exchange activity of GEFs by binding to their Dbl-homology domain (DH) (15). Essentially, the authors could identify the total concentration of active GEF as the main bifurcation parameter for the switch from stable to oscillatory states at intermediate GEF concentrations. In experiments, they vary this bifurcation parameter by treating cells with nocodazole, which leads to depolymerization of microtubules from which GEFs are then released. The crossover from stable to oscillatory dynamics happens as a function of the total GEF concentration.

## Parametrization

### Non-linear RhoA pathway

For the simulations with the non-linear Rho pathway we follow Kamps et al. (8). In Eqs. (S29) to (S31) we treat the inactive species separately with  $c_i = c_T - c$ . The inactive species diffuse faster than the active species  $D_{c,i} > D_c$ . The reaction kinetics are given by  $R_{c_i} = -R_c$ . Hence, for the non-linear system we have a total of six coupled reaction diffusion equations coupled to the PDE describing the cell layer. Fig. S1d shows the schematic of the coupled system of PDE's. The reaction diffusion system alone exhibits instabilities that lead to the emergence of traveling wave peaks. To induce an instability we impose initial conditions on the active species by adding small random fluctuations of the form

$$c_0(\mathbf{x}) = \bar{c}_0 + \delta c_0(0.5 - \mathcal{U}_{[0,1](\mathbf{x})}), \quad (\text{S32})$$

where  $\mathcal{U}_{[0,1](\mathbf{x})}$  is the probability density function of the continuous uniform distribution,  $\bar{c}_0$  the homogeneous concentration field and  $\delta c_0$  a small fluctuation. For the inactive species we set  $c_{i,0}(\mathbf{x}) = c_T - c_0(\mathbf{x})$ . Fluctuations are  $\delta G_0 = 0.05$ ,  $\delta R_0 = 0.01$  and  $\delta M_0 = 0$ . All other relevant parameters can be found in Tab. S1 or in the supplemental information of (8).

### Linearized RhoA pathway

For the parametrization of the proposed linear signaling cascade we rely on the order of magnitudes found in the respective literature. Within the limits of our simplified model the total concentrations of RhoA and myosin are irrelevant since they do not explicitly enter the reaction kinetics in the weakly activated regime. The parameters are chosen such that the steady state concentrations of RhoA and myosin are roughly 10% of the total concentration (10, 16). Further, the reaction rates are chosen such that the time course of the myosin concentration approximates the typical time course of actively generated stresses during optogenetic activation (8, 10, 17–19). The time course of the input signal was adapted to the measured CRY2 membrane recruitment and is described by a relaxation time of  $\lambda \approx 10^{-2}$  s (20). The reference values from (8) were estimated as follows. The second term in Eq. (S30) can be approximated in a weakly activated regime with  $K_{m2} \gg R$  as  $k_2 R / (K_{m2} + R) \approx k_2 R / K_{m2} \equiv b \approx 2 \text{ s}^{-1}$ . The same argument applied to the second term in

Eq. (S31) gives  $k_6 M / (K_{m6} + M) \approx k_6 M / K_{m6} \equiv s \approx 0.0051 \text{ s}^{-1}$ .  $k$  can be estimated from the first term in Eq. (S31) by  $k_5 / (K_{m5} + M_T) = \tilde{k} = 0.00465 \text{ s}^{-1}$  from which  $k = \tilde{k} R_T = 0.002 \text{ s}^{-1}$  follows. All relevant parameters are summarized in Tab. S2.

## Elastic layer

For the parametrisation of the cell and the substrate we follow the typical orders of magnitude. Cell and substrate have a Young's modulus  $E$  in the range of several kPa. For simplicity we choose  $E_c \approx E_s$ , which also reflects that cells typically adapt to the stiffness of their environment. The viscoelastic time scale  $\tau_c$  is a free parameter in the simulations and hence the viscosity of the cell layer is defined by  $\eta_c = \tau_c E_c$ . The spring stiffness density is calculated by  $Y_s = \pi E_s / L_c$  (21), where  $L_c$  is the lateral extent of a cell. All other relevant parameters are summarized in Tables S3 to S5.

## Analytical solution of the weakly activated signaling cascade

Beguerisse-Díaz et al. (22) provide a variety of analytical solutions to weakly activated signalling cascades triggered by different input signals i.e. time course of the stimulus such as step-function, Gaussian or, as in our case, an exponential decreasing perturbation. The signaling species  $x_1^*$  is activated by an external stimulus, which in turn activates species  $x_2^*$ , and so on. In a weakly activated regime and for  $x_i^*(0) = 0$  (which is the initial condition for the perturbations  $\delta r$  and  $\delta m$ ) the output function of species  $x_n^*$  is given by

$$x_n^*(t) = \left( \prod_{i=1}^n \alpha_i \right) \sum_{i=1}^n \left( \prod_{q=1, q \neq i}^n (\beta_i - \beta_q)^{-1} \right) \times \int_0^t e^{-\beta_i(t-\tau)} A(\tau) \, d\tau. \quad (\text{S33})$$

Here  $\alpha_i$  and  $\beta_i$  denote the activation and deactivation rates of each species  $i$ , respectively, and  $A(t)$  is a stimulus applied to the first species. Applied to the system of equations

$$\frac{d\delta r}{dt} = a\delta g(t) - b\delta r, \quad \frac{d\delta m}{dt} = k\delta r - s\delta m, \quad (\text{S34})$$

together with  $A(\tau) = \delta g(\tau) = g_a e^{-\lambda\tau}$  (as in the main text) this leads to

$$\delta \tilde{r}(t) = \frac{\delta r}{r_{ss}} = \frac{b\alpha}{b-\lambda} (e^{-\lambda t} - e^{-bt}), \quad (\text{S35})$$

$$\delta \tilde{m}(t) = \frac{\delta m}{m_{ss}} = b\alpha s \left( \frac{e^{-\lambda t} - e^{-bt}}{(b-s)(b-\lambda)} - \frac{e^{-\lambda t} - e^{-st}}{(b-s)(s-\lambda)} \right). \quad (\text{S36})$$

## Description of movies

**Movie S1:** Strain-dependent feedback in a cell doublet with strong coupling. Activation of the left cell leads to substantial contraction in the right cell. Although optogenetic stimulation is only applied to the left cell, the whole doublet contracts as a unit i.e. symmetrically. Parameters used as listed in Tab. S2 and Tab. S3 with  $a_{\delta\bar{q}} = 100$  and  $\tau_c = 10s$ .

**Movie S2:** Strain-dependent feedback in a cell doublet with weak coupling. Activation of the left cell leads to weak contraction in the right cell. This leads to an overall asymmetric shape deformation of the whole doublet in which the right cell gets pulled to the left. Parameters used as listed in Tab. S2 and Tab. S3 with  $a_{\delta\bar{q}} = 0.1$  and  $\tau_c = 10s$ .

**Movie S3:** Propagation of a contraction wave through a cell chain visualized by the deformation field (color code: red color corresponds to displacement to the right, blue to the left). Optogenetic activation of the left cell leads to a contraction. The coupling to the neighboring cell induces a contraction which propagates from the left end of the cell chain to the right end. Parameters used as listed in Tab. S2 and Tab. S4. Coupling and viscoelastic time scale where chosen from the transmissive regime. Red lines indicate initial cell-cell boundary positions.

**Movie S4:** Propagation of contraction wave through a tissue-like monolayer comprised of 28 cells. Here, the contractility is controlled by the non-linear Rho-pathway which in itself exhibits wave-like instabilities. The parameters are chosen according to Tab. S1 and Tab. S5. At early times, an instability is triggered in the centered cell on the left by adding small random fluctuations on the GEF and Rho component. These random fluctuations lead to several concentrated traveling wave peaks which in turn trigger GEF activation in adjacent cells through the strain-dependent coupling. Thus, a contraction wave spreads through the whole tissue activating all cells and triggering the wave-like instability. The emerging activation pattern represents the up-down symmetry of the tissue. Cells at the free edge (edge with no cell-cell boundary) strongly deform when a contraction peak gets close to the free cell edge.

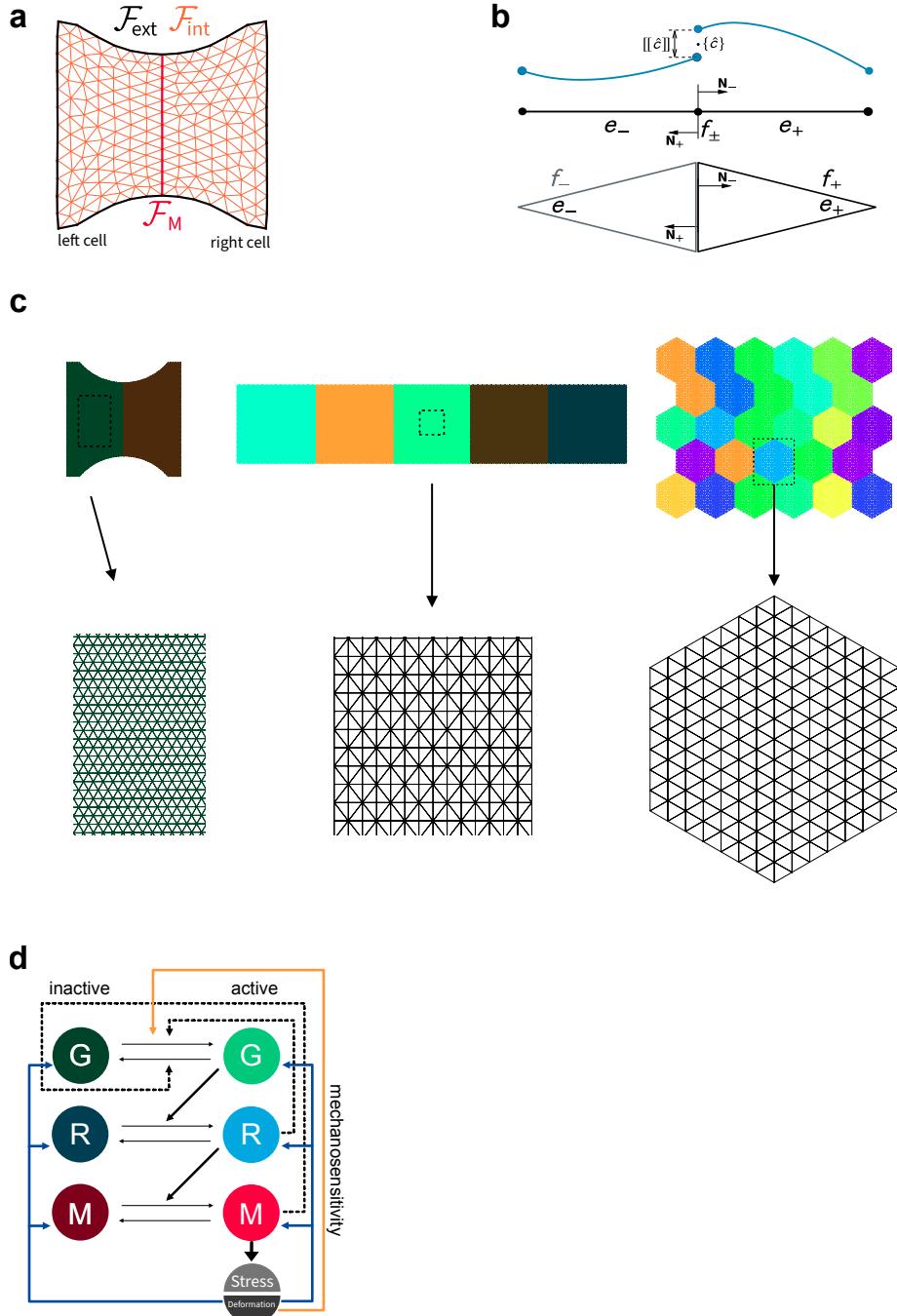


Figure S1: Panel (a) and (b) schematically explains the notation used in the derivation of the discontinuous Galerkin finite element method. Panel (c) depicts the meshes for the three cell systems. Colors highlight different cells. For cell chain and tissue-like monolayer we enforced meshes to respect the symmetry of the system's geometry. Panel (d) shows the coupled system of the non-linear RhoA pathway by Kamps et al. (8) coupled to the mechanics of the elastic layer. Mechanical feedbacks represented by yellow and blue arrows.

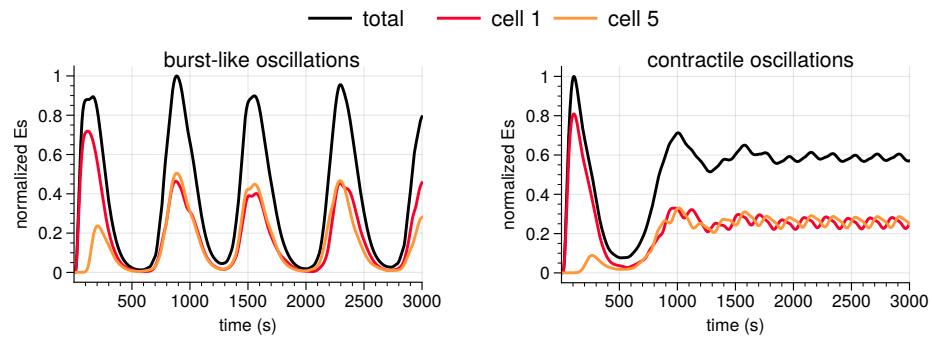


Figure S2: Different oscillations observed in a cell chain coupled to the linearized RhoA pathway. Burst-like oscillations (left) correspond to large variations in strain energy while contractile oscillations (right) corresponds to states in which the whole cell chain remains on average in a state of non-vanishing strain energy.

Abbreviation	Value
GEF	
$G_T$	0.2M
$k_3$	$1.19\text{M}^{-1}\text{s}^{-1}$
$k_4$	$3.98\text{M}^{-1}\text{s}^{-1}$
$D_G$	$0.3\text{\mu m}^2\text{s}^{-1}$
$D_{G_i}$	$9.28\text{\mu m}^2\text{s}^{-1}$
RhoA	
$R_T$	0.443M
$K_{m1}$	2.42M
$K_{m2}$	0.0745M
$k_1$	$(3.88K_{m1})\text{s}^{-1}$
$k_2$	$(2.04K_{m2})\text{Ms}^{-1}$
$D_R$	$0.3\text{\mu m}^2\text{s}^{-1}$
$D_{R_i}$	$9.28\text{\mu m}^2\text{s}^{-1}$
Myosin	
$M_T$	1.24M
$K_{m5}$	0.014M
$K_{m6}$	0.784M
$k_5$	$(0.417K_{m5})\text{s}^{-1}$
$k_6$	$(0.00509K_{m9})\text{Ms}^{-1}$
$D_M$	$0.03\text{\mu m}^2\text{s}^{-1}$
$D_{M_i}$	$0.9\text{\mu m}^2\text{s}^{-1}$

Table S1: Parameter values for the non-linear Rho pathway with fast and slow diffusing species according to (8). Here, we use M to indicate units of concentration which corresponds to  $10^6$  molecules per cell (as given in the SI of (8)).

Abbreviation	Used value	Ref. value	Reference
$\lambda$	$0.01 \text{ s}^{-1}$	$0.008 \text{ s}^{-1} - 0.018 \text{ s}^{-1}$	(20)
$\alpha$	100 %	20 % – 130 %	(20)
$b$	$0.0165 \text{ s}^{-1}$	$2 \text{ s}^{-1}$	(8)
$k$	$0.1 \text{ s}^{-1}$	$0.1408 \text{ s}^{-1}$	(10)
		$0.002 \text{ s}^{-1}$	(8)
$s$	$0.083 \text{ s}^{-1}$	$0.0051 \text{ s}^{-1}$	(8)
		$0.082 \text{ s}^{-1}$	(10)
$m_{ss}$	0.1	$0.1 - 0.8$	(10) (16)
$D_R, D_G$	$0.3 \mu\text{m}^2 \text{ s}^{-1}$	$0.28 \mu\text{m}^2 \text{ s}^{-1}$	(8)
		$0.1 \mu\text{m}^2 \text{ s}^{-1}$	(23)
$D_M$	$0.03 \mu\text{m}^2 \text{ s}^{-1}$	$0.03 \mu\text{m}^2 \text{ s}^{-1}$	(8)
		$0.01 \mu\text{m}^2 \text{ s}^{-1}$	(23)
Deduced			
$r_{ss}$	0.083		
$a$	$0.0014 \text{ s}^{-1}$	$< 0.002 \text{ s}^{-1}$	(10)

Table S2: Parameter values for the linearized RhoA signaling cascade. We set most of the parameters in accordance with the reported ranges. The parameters taken from (8) were obtained by taking the corresponding activation and deactivation rates in a weakly activated regime for which the Michaelis-Menten terms can be linearly approximated. However, their model does not provide a basal activation rate. The reported rate constants as stated in the work of Staddon et al. (10) were deduced from Michaux et al. (24). The parameters  $r_{ss}$  and  $a$  are not independent and consequently deduced from the fixed parameters.

Abbreviation	Value
Cell parameters	
Young's Modulus $E_c$	$5 \cdot 10^3 \text{ Pa}$
Poisson's ratio $\nu_c$	0.5
Cell height $h_c$	$1 \cdot 10^{-6} \text{ m}$
Lateral extent $L_c$	$45 \cdot 10^{-6} \text{ m}$
Two-dimensional active stress $\sigma_0$	$2 \cdot 10^{-3} \text{ N m}^{-1}$
Substrate parameters	
Young's Modulus $E_s$	$5 \cdot 10^3 \text{ Pa}$
Poisson's ratio $\nu_s$	0.5

Table S3: Parameter values for the simulation of the cell doublet on an H-pattern

Abbreviation	Value
Cell parameters	
Young's Modulus $E_c$	$5 \cdot 10^3 \text{ Pa}$
Poisson's ratio $\nu_c$	0.5
Cell height $h_c$	$1 \cdot 10^{-6} \text{ m}$
Lateral extent $L_c$	$40 \cdot 10^{-6} \text{ m}$
Two-dimensional active stress $\sigma_0$	$2 \cdot 10^{-3} \text{ N m}^{-1}$
Substrate parameters	
Young's Modulus $E_s$	$2.5 \cdot 10^3 \text{ Pa}$
Poisson's ratio $\nu_s$	0.5

Table S4: Parameter values for the simulation of the cell chain with continuous adhesion and unidirectional contraction.

Abbreviation	Value
Cell parameters	
Young's Modulus $E_c$	$2.5 \cdot 10^3 \text{ Pa}$
Poisson's ratio $\nu_c$	0.5
Cell height $h_c$	$1 \cdot 10^{-6} \text{ m}$
Lateral extent $L_c$	$40 \cdot 10^{-6} \text{ m}$
Two-dimensional active stress $\sigma_0$	$2.5 \cdot 10^{-3} \text{ N m}^{-1}$
Substrate parameters	
Young's Modulus $E_s$	$1 \cdot 10^3 \text{ Pa}$
Poisson's ratio $\nu_s$	0.5

Table S5: Parameter values for the simulation of the tissue-like monolayer with non-linear Rho-pathway. Here, we chose a smaller Young's modulus for the cell, a softer substrate and a slightly larger value for active stress in order to allow for more visible deformations.

# Example for python FEM-code for photoactivation of a cell doublet on H-pattern

Our model was implemented in the FEM-framework FEniCS (25). This is an example code for the photoactivation of a cell doublet with mechanochemical feedback.

```
1 # Import required libraries for finite element analysis and data processing
2 from dolfin import *          # FEniCS/DOLFIN for finite element computations
3 import numpy as np            # Numerical computations
4 import random                 # Random number generation
5 import copy                   # Deep copying of objects
6 import matplotlib.pyplot as plt # Plotting utilities
7 from ufl import tanh          # Hyperbolic tangent function
8 from numpy import savetxt     # Array saving utility
9 import pandas as pd           # Data manipulation and analysis
10 import os                     # Operating system interface
11 import csv                    # CSV file operations
12
13 """ Finite-Element-Simulation of a coupled system of reaction-diffusion equations and 2D
14 viscoelasticity
15
16 This code implements a coupled mechanochemical model for cell mechanics using FEM.
17 The model combines:
18 1. Reaction-diffusion equations for biochemical species
19 2. 2D viscoelastic mechanics for cell deformation
20 3. Mechanochemical feedback between strain and signaling
21
22 Copyright: Dennis Woerthmueller
23 Date: February 14, 2024
24 """
25
26 # Create data directory for simulation outputs
27 path_to_rawData = 'Data/'
28 if not os.path.exists(path_to_rawData):
29     os.makedirs(path_to_rawData)
30
31 # Load simulation parameters from CSV file
32 with open('inputParams.csv', newline = '') as file:
33     reader = csv.reader(file, quoting = csv.QUOTE_NONNUMERIC,
34                         delimiter = ' ')
35     rows = list(reader)
36     keys = rows[0]      # Parameter names
37     values = rows[1]    # Parameter values
38
39 # Create parameter dictionary from keys and values
40 key_value_pairs = zip(keys, values)
41 p = dict(key_value_pairs)
42
43 def calculateStrainEnergy(u, kN, dx):
44     """
45     Calculate the elastic strain energy in the substrate.
46
47     Args:
48         u (Function): Displacement field
49         kN (Expression): Spring constant field
50         dx (Measure): Integration measure
51
52     Returns:
53         float: Total strain energy
54     """
55     return assemble(0.5*kN*inner(u,u)*dx)
56
57 class KNExpression(UserExpression):
```

```

57 """
58 Define position-dependent spring constants for an H-shaped micropattern.
59
60 The pattern consists of two vertical arms connected by a horizontal crossbar.
61 Spring constants are non-zero only within the pattern.
62 """
63 def __init__(self, Y, armWidth, degree=2):
64     print("BIS HIER")
65     super().__init__()
66     self.armWidth = armWidth # Width of pattern arms
67     self.Y = Y               # Young's modulus / spring constant
68
69 def eval(self, value, x):
70     """
71     Evaluate spring constant at given position.
72
73     Args:
74         value: Output value (modified in-place)
75         x: Spatial coordinates
76     """
77     d = 1 # Domain size
78     # Set spring constant Y in arms and crossbar, 0 elsewhere
79     if (x[0] <= -(d/2)+self.armWidth or x[0] >= (d/2)-self.armWidth or
80         between(x[1], (-self.armWidth/2, self.armWidth/2))):
81         value[0] = self.Y
82     else:
83         value[0] = 0.0
84
85 def normalize_solution(U, max):
86     """
87     Normalize solution vector by dividing by maximum value.
88
89     Args:
90         U (Function): Solution vector to normalize
91         max (float): Maximum value to normalize by
92
93     Returns:
94         Function: Normalized solution vector
95     """
96     U_array = U.vector().get_local()
97     U_array /= max
98     U.vector()[:] = U_array
99     return U
100
101 def eps(v):
102     """
103     Calculate strain tensor from displacement field.
104
105     Args:
106         v (Function): Displacement field
107
108     Returns:
109         Tensor: Symmetric gradient (strain tensor)
110     """
111     return sym(grad(v))
112
113 class selectedSubdomain(UserExpression):
114     """
115     Mark specific subdomains with different values.
116     Used to identify and assign properties to different regions.
117     """
118     def __init__(self, subdomains, val_inside, val_outside, subdomain_id, **kwargs):
119         super().__init__()
120         self.subdomains = subdomains           # Subdomain markers
121         self.val_inside = val_inside          # Value inside selected subdomain
122         self.val_outside = val_outside        # Value outside selected subdomain

```

```

123         self.subdomain_id = subdomain_id      # ID of subdomain to mark
124
125     def eval_cell(self, values, x, cell):
126         """
127             Evaluate marker value for each cell.
128
129             Args:
130                 values: Output value (modified in-place)
131                 x: Spatial coordinates
132                 cell: Current cell
133
134             if self.subdomains[cell.index] == self.subdomain_id:
135                 values[0] = self.val_inside
136             else:
137                 values[0] = self.val_outside
138
139     class SquareCompartmentDoublet(UserExpression):
140         """
141             Define square compartment for cell doublet simulation.
142             Used to create initial conditions and activation patterns.
143
144         def __init__(self, A, d, degree=0):
145             super().__init__()
146             self.A = A # Amplitude
147             self.d = d # Distance/size parameter
148
149         def eval(self, value, x):
150             """
151                 Evaluate compartment value at given position.
152
153             Args:
154                 value: Output value (modified in-place)
155                 x: Spatial coordinates
156
157             if (x[0] <= -self.d):
158                 value[0] = self.A
159             else:
160                 value[0] = 0.0
161
162     def get_boundary_of_deformed_mesh(u, geo_file_name):
163         """
164             Extract boundary coordinates of deformed mesh.
165             Used for tracking boundary deformation over time.
166
167             Args:
168                 u (Function): Displacement field
169                 geo_file_name (str): Base name of geometry files
170
171             Returns:
172                 numpy.array: Sorted boundary coordinates
173
174             # Load mesh and boundary definitions
175             dummy_mesh = Mesh("%s.xml"% (geo_file_name))
176             boundaries = MeshFunction("size_t", dummy_mesh, "%s_facet_region.xml"% (geo_file_name))
177             subdomains = MeshFunction("size_t", dummy_mesh, "%s_physical_region.xml"% (geo_file_name))
178
179             # Apply displacement to mesh
180             ALE.move(dummy_mesh, u)
181             V_mesh = FunctionSpace(dummy_mesh, "CG", 1)
182             v2d = vertex_to_dof_map(V_mesh)
183
184             # Extract boundary vertices
185             dofs = []
186             for facet in facets(dummy_mesh):
187                 if boundaries[facet.index()] == 2: # Top boundary
188                     vertices = facet.entities(0)

```

```

189         for vertex in vertices:
190             dofs.append(v2d[vertex])
191
192     # Sort and return boundary coordinates
193     unique_dofs = np.array(list(set(dofs)), dtype=np.int32)
194     boundary_coords = V_mesh.tabulate_dof_coordinates()[unique_dofs]
195     col = 0
196     boundary_coords_sorted = boundary_coords[np.argsort(boundary_coords[:, col])]
197     return boundary_coords_sorted
198
199 def DGWeakFormRD(c, cn, vc, Dc, u, J, J_n, F, n, dx, dS, dSM, dt, cellularisation=True):
200     """
201     Construct weak form for reaction-diffusion equations using Discontinuous Galerkin method.
202
203     Args:
204         c (Function): Current concentration
205         cn (Function): Previous concentration
206         vc (TestFunction): Test function
207         Dc (float): Diffusion coefficient
208         u (Function): Displacement field
209         J (Expression): Current Jacobian
210         J_n (Expression): Previous Jacobian
211         F (Expression): Deformation gradient
212         n (Expression): Normal vector
213         dx (Measure): Volume measure
214         dS (Measure): Interior facet measure
215         dSM (Measure): Interface measure
216         dt (float): Time step
217         cellularisation (bool): Whether to include cell interface terms
218
219     Returns:
220         Form: Complete weak form for reaction-diffusion equation
221     """
222     # Calculate geometric quantities
223     F_inv = inv(F)
224     F_inv_T = inv(F).T
225     I = Identity(2)
226     eps = sym(grad(u))
227
228     # Numerical parameters
229     h = 0.1    # Mesh size parameter
230     sN = 50    # Penalty parameter
231
232     # Modified diffusion tensor including geometric factors
233     alph = J*(I-2*eps)*Dc
234
235     # Calculate interface terms for DG formulation
236     delt_p = dot(n('+'), alph('+')*n('+'))
237     delt_m = dot(n('-'), alph('-')*n('-'))
238
239     # Weights for averaging
240     w_pos = delt_m/(delt_p+delt_m)
241     w_neg = delt_p/(delt_p+delt_m)
242
243     # Average terms for concentration gradients
244     grad_c_avg_term = w_pos*alph('+')*grad(c)('+'')+w_neg*alph('-')*grad(c)('-'')
245     grad_vc_avg_term = w_pos*alph('+')*grad(vc)('+'')+w_neg*alph('-')*grad(vc)('-'')
246
247     # Interface penalty parameter
248     gamma = 2*delt_p*delt_m/(delt_p+delt_m)
249
250     # Time derivative terms
251     time_deriv = J*(c-cn)/dt*vc*dx+(J-J_n)/dt*c*vc*dx
252
253     # Standard diffusion term
254     standard = dot(alph * grad(c), grad(vc)) * dx

```

```

255
256     # Interface terms based on cellularisation flag
257     if cellularisation:
258         # Terms for internal cell boundaries
259         consistency = -dot(jump(vc,n),grad_c_avg_term)*dS + dot(jump(vc,n),grad_c_avg_term)*dSM
260         symmetry = - dot(grad_vc_avg_term, jump(c,n))*dS + dot(grad_vc_avg_term,jump(c,n))*dSM
261         penalty = sN/h*gamma*dot(jump(vc, n), jump(c,n))* dS - sN/h*gamma*dot(jump(vc,n), jump(c, n))*dSM
262     else:
263         # Terms without internal boundaries
264         consistency = -dot(jump(vc,n),grad_c_avg_term)*dS
265         symmetry = - dot(grad_vc_avg_term, jump(c,n))*dS
266         penalty = sN/h*gamma*dot(jump(vc, n), jump(c,n))* dS
267
268     # Combine all terms
269     weakForm = time_deriv + standard + consistency + symmetry + penalty
270
271     return weakForm
272
273 # Output file names
274 name = 'simulation_output'           # Name of the output xdmf-file
275 geo_file_name = 'cell_doublet_shape_nonDim' # Name of gmsh .geo-file
276
277 def simulation():
278     """
279     Main simulation function implementing a mechanochemical feedback model.
280
281     The simulation couples three main components:
282     1. Reaction-diffusion system for GEF-RhoA-Myosin signaling
283     2. Viscoelastic mechanics for cell deformation
284     3. Mechanochemical feedback through strain
285
286     Uses mixed finite elements: DG for concentrations, CG for displacement.
287     """
288     # -----
289     # Initialize mesh and finite element structures
290     # -----
291     # Convert mesh from Gmsh format to FEniCS XML format
292     if not os.path.exists('%s.xml'%(geo_file_name)):
293         os.system('dolfin-convert %s.msh %s.xml'%(geo_file_name,geo_file_name))
294
295     # Load mesh and domain definitions
296     mesh = Mesh("%s.xml"%(geo_file_name))
297     boundaries = MeshFunction("size_t", mesh, "%s_facet_region.xml"%(geo_file_name))
298     subdomains = MeshFunction("size_t", mesh, "%s_physical_region.xml"%(geo_file_name))
299
300     # Save domain definitions for visualization
301     file_results = XDMFFile("subdomains.xdmf")
302     file_results.write(subdomains)
303     file_results = XDMFFile("boundaries.xdmf")
304     file_results.write(boundaries)
305
306     # Define measures for integration
307     dx = Measure('dx', domain=mesh, subdomain_data=subdomains)      # Volume measure
308     ds_all = Measure('ds', subdomain_data=boundaries)              # Surface measure
309     dSM = ds_all(1)                                                 # No-flux interface measure
310
311     # Initialize domain markers
312     cell1 = selectedSubdomain(subdomains, 1, 0, subdomain_id = 1, degree=0)      # Active cell
313     non_opto_cell = selectedSubdomain(subdomains, 0, 1, subdomain_id = 1, degree=0) # Non-
314     photoactivated cell
315     n = FacetNormal(mesh)                                              # Normal vector
316
317     # Define finite elements for mixed formulation
318     P1 = FiniteElement('DG', triangle, 1)          # DG elements for concentrations

```

```

318 P2 = VectorElement('CG', triangle, 1)           # CG elements for displacement
319 element = MixedElement([P1, P1, P1,P2])        # Combined element
320 V = FunctionSpace(mesh, element)               # Mixed function space
321
322 # Initialize function spaces for output fields
323 # DG spaces for scalar fields
324 dFE_DG0 = FiniteElement("DG", mesh.ufl_cell(), 0)
325 dFE_DG1 = FiniteElement("DG", mesh.ufl_cell(), 1)
326 dFE_CG1 = FiniteElement("CG", mesh.ufl_cell(), 1)
327 dFE_CG2 = FiniteElement("CG", mesh.ufl_cell(), 2)
328
329 # Tensor spaces for stress/strain fields
330 TensorSpace_DG0 = TensorFunctionSpace(mesh, "DG", 0)
331 TensorSpace_DG1 = TensorFunctionSpace(mesh, "DG", 1)
332 TensorSpace_CG1 = TensorFunctionSpace(mesh, "CG", 1)
333 TensorSpace_CG2 = TensorFunctionSpace(mesh, "CG", 2)
334
335 # Create function spaces
336 W_DG0 = TensorSpace_DG0      # DG0 tensor space
337 W_DG1 = TensorSpace_DG1      # DG1 tensor space
338 W_CG1 = TensorSpace_CG1      # CG1 tensor space
339 W_CG2 = TensorSpace_CG2      # CG2 tensor space
340
341 # Scalar function spaces
342 K_DG0 = FunctionSpace(mesh, dFE_DG0)
343 K_DG1 = FunctionSpace(mesh, dFE_DG1)
344 K_CG1 = FunctionSpace(mesh, dFE_CG1)
345 K_CG2 = FunctionSpace(mesh, dFE_CG2)
346
347 # Vector function space for displacement
348 V_CG1 = VectorFunctionSpace(mesh, "CG",1)
349
350 # Initialize output functions
351 # Vector fields (displacement and traction)
352 disp = Function(V_CG1, name='Displacement')
353 TractionF = Function(V_CG1, name='Traction')
354
355 # Scalar fields for molecular species
356 GEF = Function(K_DG0, name='GEF')                # GEF concentration
357 RhoA = Function(K_DG0, name='RhoA')              # RhoA concentration
358 Myosin = Function(K_DG0, name='Myosin')          # Myosin concentration
359 GEF_inactive = Function(K_DG0, name='GEF inactive')
360 RhoA_inactive = Function(K_DG0, name='RhoA inactive')
361 Myosin_inactive = Function(K_DG0, name='Myosin inactive')
362
363 # Scalar fields for mechanics
364 activatedCell = Function(K_DG0, name='Activated Cell')
365 nonOptoCells = Function(K_DG0, name='Non-opto Cells')
366 pattern = Function(K_DG0, name='Micropattern')
367 Jacobian = Function(K_DG0, name='detF')
368 JacobianPositive = Function(K_DG0, name='detF +')
369 feedbackPositive = Function(K_DG0, name='feedback')
370 hypTangentPositive = Function(K_DG0, name='tanh')
371 traceGreenLagrange = Function(K_DG0, name='trE')
372 traceGreenLagrangePositive = Function(K_DG0, name='trE +')
373 detCauchyStressPositive = Function(K_DG0, name='det(CS) +')
374
375 # Tensor fields for stress and strain
376 Cauchystress = Function(W_DG0, name='Cauchy Stress')
377 Cauchystress_passive = Function(W_DG0, name='Passive Cauchy Stress')
378 Pstress = Function(W_DG0, name='Piola Stress')
379 Pstress_passive = Function(W_DG0, name='Passive Piola Stress')
380 activeStress = Function(W_DG0, name='Active Stress')
381 strainGreenLagrange = Function(W_DG0, name='E (GL Strain)')
382 defGrad_save = Function(W_DG0, name='Deformation Gradient Tensor')
383 CauchyGreenInverse_save = Function(W_DG0, name='Inverse Cauchy Green')

```

```

384
385     # Diffusion tensors
386     diffTensor_G = Function(W_DG0, name='alpha_G')
387     diffTensor_R = Function(W_DG0, name='alpha_R')
388     diffTensor_M = Function(W_DG0, name='alpha_M')
389
390     # Initialize output file
391     xdmf_file = XDMFFFile(path_to_rawData+"%s.xdmf"%(name))
392     xdmf_file.parameters["flush_output"] = True
393     xdmf_file.parameters["functions_share_mesh"] = True
394
395     # Define spring constant field for substrate
396     kN = KNExpression(p['Ys_N'], p['armWidth_N'], degree=2)
397
398     # Set time discretization parameters
399     DT = 0.5                      # Time step size
400     dt = Constant(DT)            # FEniCS constant for time step
401     t = DT                        # Current time
402     T = 500                       # End time
403     t_opto = 5                   # photoactivation
404
405     # Initialize variational problem components
406     dU = TrialFunction(V)        # Trial function
407     U_tot = Function(V)          # Current solution
408     U_tot_n = Function(V)        # Previous solution
409     vG, vR, vM, vu = TestFunctions(V) # Test functions
410
411     # Additional functions for solution storage
412     U_tot_save = Function(V)
413     u_save = Function(V_CG1)
414     U_tot_save_n = Function(V)
415
416     # Set initial conditions
417     u0 = Constant((0.0,0.0))    # Zero displacement
418     random.seed()                # Set random seed
419     G_0 = Constant(0)           # Initial GEF concentration
420     R_0 = Constant(0)           # Initial RhoA concentration
421     M_0 = Constant(0)           # Initial Myosin concentration
422
423     # Project initial conditions to appropriate function spaces
424     uG_n = project(G_0, V.sub(0).collapse())
425     uR_n = project(R_0, V.sub(1).collapse())
426     uM_n = project(M_0, V.sub(2).collapse())
427     u_n = project(u0, V.sub(3).collapse())
428
429     # Assign initial conditions to solution vector
430     assign(U_tot_n, [uG_n,uR_n,uM_n,u_n])
431
432     # Split solution for component access
433     uG,uR, uM, u = split(U_tot)      # Current solution
434     uG_n, uR_n, uM_n, u_n = split(U_tot_n) # Previous solution
435
436     # Initialize arrays for storing results
437     time_array = []
438     strainEnergyLeft_vs_time = []
439     strainEnergyRight_vs_time = []
440     strainEnergyTotal_vs_time = []
441     boundary_curve_vs_time = []
442
443
444     # Main time stepping loop
445     while t <= T:
446         print("TIME = ", t)
447
448         # -----

```

```

450     # Set up tensors for continuum description of the cell layer
451     #
452     # Define fundamental geometric tensors
453     I = Identity(2)                                # Identity tensor
454     F = I + grad(u)                                # Deformation gradient tensor
455     J_n = 1+tr(grad(u_n))                          # Previous Jacobian (volume change)
456     J = 1+tr(grad(u))                            # Current Jacobian
457     F_transpose = F.T                             # Transpose of deformation gradient
458     F_inv = I - grad(u)                           # Approximate inverse of deformation gradient
459     C = I - 2*sym(grad(u))                      # Right Cauchy-Green tensor
460     C1 = inv(C)                                 # Inverse of Cauchy-Green tensor
461
462     # Calculate strain measures
463     eps_n = sym(grad(u_n))                      # Previous strain tensor
464     eps = sym(grad(u))                           # Current strain tensor
465     trace_n = tr(eps_n)                          # Previous volumetric strain
466     trace = tr(eps)                            # Current volumetric strain
467
468     #
469     # Define active stresses from myosin activity
470     #
471     # Calculate myosin-dependent active stress
472     activeStress_from_myosin = p['sig_a_N']* tanh(1*uM)    # Nonlinear myosin activation
473     # Convert to tensor form (isotropic active stress)
474     activeStress_tensor = activeStress_from_myosin*as_tensor([[1, 0], [0, 1]])
475
476     #
477     # Constitutive relations for viscoelastic material
478     #
479     # Total Cauchy stress including active and passive components
480     CS = (activeStress_tensor +
481           p['lmbdaE_N'] * tr(eps) * Identity(2) +          # Active stress
482           2*p['muE_N']*eps +                               # Elastic volumetric
483           p['tauc']*p['lmbdaE_N']*(trace-trace_n)/dt*Identity(2) + # Viscous volumetric
484           2*p['muE_N']*p['tauc']*(eps-eps_n)/dt)        # Viscous deviatoric
485
486     # Passive component of Cauchy stress
487     CS_passive = (p['lmbdaE_N'] * tr(eps) * Identity(2) +      # Elastic volumetric
488                    2*p['muE_N']*eps +                         # Elastic deviatoric
489                    p['tauc']*p['lmbdaE_N']*(trace-trace_n)/dt*Identity(2) + # Viscous volumetric
490                    2*p['muE_N']*p['tauc']*(eps-eps_n)/dt)        # Viscous deviatoric
491
492     # Calculate positive and negative parts for mechanochemical feedback
493     trace_positive = conditional(gt(trace,0),trace,0)*non_opto_cell    # Positive strain
494     trace_negative = conditional(gt(0,trace),trace,0)*non_opto_cell    # Negative strain
495     J_positive = conditional(gt(J-1,0),J-1,0)*non_opto_cell          # Positive volume change
496     detCS_positive = conditional(gt(0,det(CS_passive)),det(CS_passive),0) # Positive stress
497 determinant
498
499     # Calculate traction force
500     tF = kN*u                                     # Linear spring force
501     tF_mag = kN*sqrt(inner(u,u))                 # Magnitude of traction force
502     tF_mag_projected = project(tF_mag, K_DG0)   # Project for visualization
503
504     #
505     # Handle photoactivation event
506     #
507     if t == t_opto:
508         # Initialize photoactivation pattern
509         G_0 = Constant(p['alpha'])*SquareCompartmentDoublet(1,5e-6/p['length_scale'])
510
511         # Set and project new initial conditions after photoactivation
512         uG_n = project(G_0, V.sub(0).collapse())
513         uR_n = project(R_0, V.sub(1).collapse())
514         uM_n = project(M_0, V.sub(2).collapse())
515         u_n = project(u0, V.sub(3).collapse())

```

```

515
516     # Update solution vector
517     assign(U_tot_n, [uG_n,uR_n,uM_n,u_n])
518     uG_n, uR_n, uM_n, u_n = split(U_tot_n)
519
520     # -----
521     # Define mechanochemical feedback
522     # -----
523     # Check cellularisation parameter
524     cellularisation = int(p['cellularisation'])
525
526     # Calculate feedback based on positive strain in non-activated cells
527     if cellularisation:
528         feedback = p['fb']*trace_positive*non_opto_cell
529     else:
530         feedback = Constant(0)
531
532     # Disable feedback if feedback strength is small
533     if p['fb'] < 0.01:
534         feedback = Constant(0)
535
536     # -----
537     # Define reaction kinetics for signaling cascade
538     # -----
539     # GEF activation/inactivation with mechanical feedback
540     React_G = -p['lambda_decay']*uG + feedback
541     # RhoA activation by GEF
542     React_R = p['b']*(uG - uR)
543     # Myosin activation by RhoA
544     React_M = p['s']*(uR - uM)
545
546     # -----
547     # Construct weak form of the coupled system
548     # -----
549     # Reaction-diffusion equations with DG formulation
550     FcG = DGWeakFormRD(uG,uG_n,vG,p['DG_N'],u,J,J_n,F,n,dx,dS,dSM,dt,cellularisation) -J*(React_G)
551     *vG*dx
552     FcR = DGWeakFormRD(uR,uR_n,vR,p['DR_N'],u,J,J_n,F,n,dx,dS,dSM,dt,cellularisation) -J*(React_R)
553     *vR*dx
554     FcM = DGWeakFormRD(uM,uM_n,vM,p['DM_N'],u,J,J_n,F,n,dx,dS,dSM,dt,cellularisation) -J*(React_M)
555     *vM*dx
556
557     # Mechanical equilibrium equation
558     F_u = inner(CS,grad(vu))*dx + kN*inner(u,vu)*dx
559
560     # -----
561     # Complete weak form
562     FWF = FcG + FcR + FcM + F_u
563
564     # -----
565     # Configure and solve the nonlinear system
566     # -----
567     # Set solver parameters for SNES (nonlinear solver)
568     snes_solver_parameters = {
569         "nonlinear_solver": "snes",
570         "snes_solver": {
571             "linear_solver": "lu",          # Direct LU solver for linear system
572             'absolute_tolerance': 1e-6,    # Convergence criteria
573             'relative_tolerance': 1e-6,
574             "maximum_iterations": 20,      # Limit iteration count
575             "report": True,               # Print convergence info
576             "error_on_nonconvergence": True
577         }
578     }
579
580     # Set up nonlinear variational problem
581     dFWF = derivative(FWF, U_tot, dU)   # Calculate Jacobian

```

```

578     problem = NonlinearVariationalProblem(FWF, U_tot, [], J=dFWF)
579     solver = NonlinearVariationalSolver(problem)
580     solver.parameters.update(snes_solver_parameters)
581     info(solver.parameters, False)
582
583     # Solve the system
584     (iter, converged) = solver.solve()
585
586
587
588
589     # -----
590     # Prepare and save solution fields for visualization
591     # -----
592     # Copy current solutions for post-processing
593     U_tot_save.assign(U_tot)                      # Current solution
594     U_tot_save_n.assign(U_tot_n)                  # Previous solution
595     _uG, _uR, _uM, _u = U_tot_save.split(deepcopy=True) # Split into components
596
597     # -----
598     # Project solution fields onto appropriate function spaces
599     # -----
600     # Vector fields (CG1 space)
601     disp.assign(project(_u, V_CG1))            # Displacement field
602     TractionF.assign(project(tF, V_CG1))        # Traction force
603
604     # Molecular species concentrations (DG0 space)
605     GEF.assign(project(_uG, K_DG0))             # GEF concentration
606     RhoA.assign(project(_uR, K_DG0))            # RhoA concentration
607     Myosin.assign(project(_uM, K_DG0))           # Myosin concentration
608
609     # Domain markers and geometric quantities (DG0 space)
610     activatedCell.assign(project(cell1, K_DG0))    # Activated cell region
611     nonOptoCells.assign(project(non_opto_cell, K_DG0)) # Non-photoactivated regions
612     pattern.assign(project(kN, K_DG0))            # Micropattern
613     Jacobian.assign(project(J, K_DG0))            # Volume change
614     JacobianPositive.assign(project(J_positive, K_DG0)) # Positive volume change
615     feedbackPositive.assign(project(feedback, K_DG0)) # Mechanical feedback
616
617     # Strain measures (DG0 space)
618     traceGreenLagrange.assign(project(trace, K_DG0))          # Volumetric strain
619     traceGreenLagrangePositive.assign(project(trace_positive, K_DG0)) # Positive strain
620     detCauchyStressPositive.assign(project(detCS_positive, K_DG0)) # Positive stress
621
622     # Stress and strain tensors (DG0 tensor space)
623     Cauchystress.assign(project(CS, W_DG0))                # Total Cauchy stress
624     Cauchystress_passive.assign(project(CS_passive, W_DG0)) # Passive stress
625     activeStress.assign(project(activeStress_tensor, W_DG0)) # Active stress
626     strainGreenLagrange.assign(project(eps, W_DG0))         # Strain tensor
627     defGrad_save.assign(project(F, W_DG0))                 # Deformation gradient
628     CauchyGreenInverse_save.assign(project(C1, W_DG0))       # Inverse Cauchy-Green tensor
629
630     # -----
631     # Write fields to XDMF file for visualization
632     # -----
633     # Vector fields
634     xdmf_file.write(disp, t)                            # Displacement
635     xdmf_file.write(TractionF, t)                      # Traction
636
637     # Molecular concentrations
638     xdmf_file.write(GEF, t)                           # GEF
639     xdmf_file.write(RhoA, t)                          # RhoA
640     xdmf_file.write(Myosin, t)                        # Myosin
641
642     # Domain markers and geometric quantities
643     xdmf_file.write(activatedCell, t)                 # Activated cells

```

```

644     xdmf_file.write(nonOptoCells, t)           # Non-photoactivated cells
645     xdmf_file.write(pattern, t)                # Micropattern
646     xdmf_file.write(Jacobian, t)               # Volume change
647     xdmf_file.write(JacobianPositive, t)      # Positive volume change
648     xdmf_file.write(feedbackPositive, t)       # Mechanical feedback
649
650     # Strain measures
651     xdmf_file.write(traceGreenLagrange, t)      # Total strain
652     xdmf_file.write(traceGreenLagrangePositive, t) # Positive strain
653     xdmf_file.write(detCauchyStressPositive, t) # Positive stress
654
655     # Stress and strain tensors
656     xdmf_file.write(Cauchystress, t)             # Total stress
657     xdmf_file.write(Cauchystress_passive, t)      # Passive stress
658     xdmf_file.write(activeStress, t)              # Active stress
659     xdmf_file.write(strainGreenLagrange, t)        # Strain tensor
660     xdmf_file.write(defGrad_save, t)               # Deformation gradient
661     xdmf_file.write(CauchyGreenInverse_save, t)    # Inverse Cauchy-Green
662
663     # -----
664     # Calculate and store derived quantities
665     # -----
666     # Store current time
667     time_array.append(t)
668
669     # Calculate strain energy in different regions
670     dx1 = Measure('dx', domain=mesh, subdomain_data=subdomains, subdomain_id=1)
671     strainEnergyLeft = calculateStrainEnergy(u, kN, dx1)          # Left cell
672
673     dx2 = Measure('dx', domain=mesh, subdomain_data=subdomains, subdomain_id=2)
674     strainEnergyRight = calculateStrainEnergy(u, kN, dx2)         # Right cell
675
676     strainEnergyTotal = calculateStrainEnergy(u, kN, dx)          # Total system
677
678     # Extract boundary curve for shape analysis
679     boundary_curve = get_boundary_of_deformed_mesh(_u, geo_file_name)
680
681     # Store energy and boundary data
682     strainEnergyLeft_vs_time.append(strainEnergyLeft)
683     strainEnergyRight_vs_time.append(strainEnergyRight)
684     strainEnergyTotal_vs_time.append(strainEnergyTotal)
685     boundary_curve_vs_time.append(boundary_curve)
686
687     # -----
688     # Update time step and solution
689     # -----
690     t = t + DT           # Increment time
691     U_tot_n.assign(U_tot) # Store current solution for next step
692
693     # -----
694     # Save simulation data to files
695     # -----
696     # Create dictionary of energy data
697     outputDict = {
698         'time': np.array(time_array),
699         'strainEnergyLeft': np.array(strainEnergyLeft_vs_time),
700         'strainEnergyRight': np.array(strainEnergyRight_vs_time),
701         'strainEnergyTotal': np.array(strainEnergyTotal_vs_time)
702     }
703
704     # Save energy data to CSV
705     pd.DataFrame.from_dict(data=outputDict).to_csv(path_to_rawData+'strainEnergy.csv', header=True)
706
707     # Save boundary curve data to NPZ file
708     np.savez(path_to_rawData + 'boundary_curve.npz',

```

```

709         boundary_curve=boundary_curve_vs_time,
710         time=np.array(time_array))
711
712 # Execute simulation if script is run directly
713 if __name__ == "__main__":
714     simulation()

```

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