

Central dogma at the single-molecule level in living cells

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Gene expression originates from individual DNA molecules within living cells. Like many single-molecule processes, gene expression and regulation are stochastic, that is, sporadic in time. This leads to heterogeneity in the messenger-RNA and protein copy numbers in a population of cells with identical genomes. With advanced single-cell fluorescence microscopy, it is now possible to quantify transcriptomes and proteomes with single-molecule sensitivity. Dynamic processes such as transcription-factor binding, transcription and translation can be monitored in real time, providing quantitative descriptions of the central dogma of molecular biology and the demonstration that a stochastic single-molecule event can determine the phenotype of a cell.

This year marks the thirty-fifth anniversary of single-molecule optical detection and imaging. In 1976, Thomas Hirschfeld successfully detected single molecules at room temperature using an optical microscope to reduce probe volume and hence the background signal¹. Figure 1a shows his one-dimensional (1D) fluorescence image of individual immobilized protein molecules, each labelled with tens of fluorophores. The use of tightly focused laser beams eventually allowed single-fluorophore detection in solution phase at room temperature, more than a decade later². The imaging of single fluorophores in ambient environments was first reported with a scanning probe method³, and was followed by much easier and improved methods^{4–8} akin to Hirschfeld's, which remain the methods of choice for imaging single molecules. In the past decade, improvements in photodetectors and optical components have allowed extensive single-molecule fluorescence studies on a variety of biological problems, first *in vitro* and more recently in living cells.

In a single-molecule experiment, one often observes stochastic behaviour, which would otherwise be obscured in an ensemble measurement. Figure 1b shows an early real-time observation of enzymatic turnovers of a single enzyme molecule, cholesterol oxidase⁹. The enzyme contains a flavin moiety that is naturally fluorescent in its oxidized form, but not in its reduced form. Each on/off cycle of fluorescence emission corresponds to an enzymatic turnover. This time trace resembles the electrical signal of a single ion channel recorded using a patch clamp — the first single-molecule technique in biology¹⁰. However, in this case, stochastic chemical reaction events of a single enzyme molecule are seen. Here, stochastic means that each fluorescence on/off time is probabilistic. Unlike the deterministic chemical kinetics of ensembles, each time trace is different, although their statistical properties are reproducible. On a single-molecule basis, when a chemical reaction occurs, a chemical bond is formed in less than 1 ps and the process cannot be resolved in a single-molecule experiment. However, the waiting time for the event is much longer and is probabilistic. When the kinetic scheme of a reaction includes a rate-limiting step, the distribution of the waiting times follows a single exponential distribution, and the number of events in a fixed time interval follows a Poisson distribution.

By contrast, if the overall reaction does not have one rate-limiting step but instead consists of identical sequential steps, the total waiting

time is less stochastic. An example of this is DNA replication by a single DNA polymerase, which is the basis of single-molecule sequencing¹¹, a key application of single-molecule enzymology in biotechnology. A stochastic time trace of individual nucleotides incorporated into a single-stranded DNA template by a single DNA polymerase molecule is shown in Fig. 1c. Although the waiting time for each base incorporation step is exponentially distributed, the total waiting time for replicating the long DNA is narrowly distributed¹² — a consequence of the central limit theorem. Bacterial cell-cycle time, when limited by chromosome replication, is not stochastic for this reason¹³. The experiments in Fig. 1b, c were conducted under non-equilibrium steady-state conditions, in which the substrate concentration (thermodynamic driving force) does not change while substrate molecules are continuously converted to product molecules. This is similar to many non-equilibrium processes in a living cell, such as gene expression.

The central dogma of molecular biology states that genetic information encoded in DNA is transcribed to mRNA by RNA polymerases, and mRNA is translated to protein by ribosomes. In a living cell, DNA exists as individual molecules from which the regulation of gene expression originates. But our knowledge of gene expression has come mainly from genetic and biochemical studies conducted with large populations of cells and purified biomolecules, which often obscure the single-molecule nature of gene expression. In recent years, single-molecule experiments *in vitro* have provided mechanistic insight into the functions of macromolecules involved in gene expression, including transcriptional and translational machineries^{14–18}. Compelling areas of further investigation involve the observation and quantitative description of gene expression and regulation in a living cell.

Not only is there only one copy (or a few copies) of a particular gene, but the copy number of a particular mRNA is also small owing to short intracellular mRNA lifetimes¹⁹, at least in a bacterial cell. The copy number of particular proteins ranges from zero to 10,000 (refs 20, 21); many important proteins, such as transcription factors, which regulate gene expression, have small copy numbers²². Consequently, single-molecule sensitivity for mRNA and protein is needed to quantify gene expression in individual cells.

Because of the stochasticity associated with the single or low copy-number macromolecules, the gene expression of individual cells cannot be synchronized. It is therefore necessary to make real-time

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observations of gene expression and regulation in single living cells. In particular, stochastic binding or unbinding of transcription factors to a particular gene, when rate limiting, must result in stochastic mRNA production, just like the single enzyme traces in Fig. 1b, c. Stochastic degradation of individual mRNA molecules further contributes to fluctuations in protein production. These temporal fluctuations of the mRNA and protein numbers (see sketches in Fig. 2) result in cell-to-cell variation of the copy numbers, or gene expression 'noise'. Under the steady-state condition, the connection between temporal fluctuations and variation within the population is similar to ergodicity in statistical physics — the time average of a system equals the ensemble average of identical systems.

Here we review recent single-molecule experiments that provide quantitative descriptions of the central dogma in living bacterial cells, although the strategies and technical advances highlighted are applicable to future studies in eukaryotic cells. We show that single-molecule stochastic events have important biological consequences, such as determining the phenotype of a cell.

Imaging single molecules in living cells

To image a particular biomolecule in a living cell with fluorescence microscopy, specific labelling is required. The advent of genetically encodable fluorescent proteins has provided the highest specificity so far, with minimal perturbation for live-cell imaging²³, allowing real-time observations of fusion proteins of interest. Although the weak signal of a single fluorescent-protein molecule is detectable *in vitro* using a fluorescent microscope together with a combination of laser excitation and modern charge-coupled-device detectors (Fig. 3a), the detection of single fluorescent-protein reporters in living cells is challenging owing to strong cellular autofluorescence. This obstacle can be partly overcome by selecting fluorescent proteins that are spectrally separated from the autofluorescence, which is generally blue-green²⁴. Yellow- or red-emitting fluorescent proteins are therefore favourable for live-cell single-molecule imaging. Furthermore, in the same spirit as Hirschfeld's experiment, the signal can be improved by reducing the detection volume to minimize autofluorescence background. For example, total internal reflection fluorescence microscopy (TIRFM) can limit the axial depth by illuminating with an evanescent wave that penetrates only a few hundred nanometres into a sample (Fig. 3b). TIRFM is therefore ideal for studying membrane protein dynamics^{25,26}, but it does not allow imaging of the whole cell body. However, single fluorescent-protein imaging using wide-field illumination is possible in bacterial cells owing to their compact sizes (Fig. 3a).

In living eukaryotic cells, imaging a single fluorescent protein is more difficult. A typical mammalian nucleus is 5–10 μm in diameter, compared with 1 μm for a bacterial cell. In a wide-field microscope, such a large cell volume gives rise to a strong out-of-focus autofluorescence signal, which overwhelms the signal of a single fluorescent protein. Probing DNA–protein interactions therefore requires three-dimensional (3D) sectioning. Although confocal fluorescence microscopy with one-photon excitation could be used, it also causes photobleaching outside the focal plane²⁷. One solution to this problem is to use two-photon fluorescence microscopy^{28,29} (Fig. 3c), which allows localized excitation only at the laser focus, considerably reducing out-of-focus photobleaching while providing 3D sectioning in living eukaryotic cells. But, like confocal microscopy, it requires point scanning, thus limiting its time resolution. Alternatively, sheet illumination^{30,31}, in which a thin light sheet illuminates only the image plane (Fig. 3d), provides low fluorescence background and high sensitivity, as well as high temporal resolution, because it does not require point scanning. These techniques are being adapted for single-fluorescent-protein imaging in living eukaryotic cells.

In a bacterial cell, a freely diffusing protein is difficult to image because its fast diffusion spreads the signal throughout the whole cell^{32,33}. However, if a single fluorescent protein is localized, it can be imaged above the cellular autofluorescence background³⁴. This method, termed detection by localization (Fig. 4a), works as long as there is only

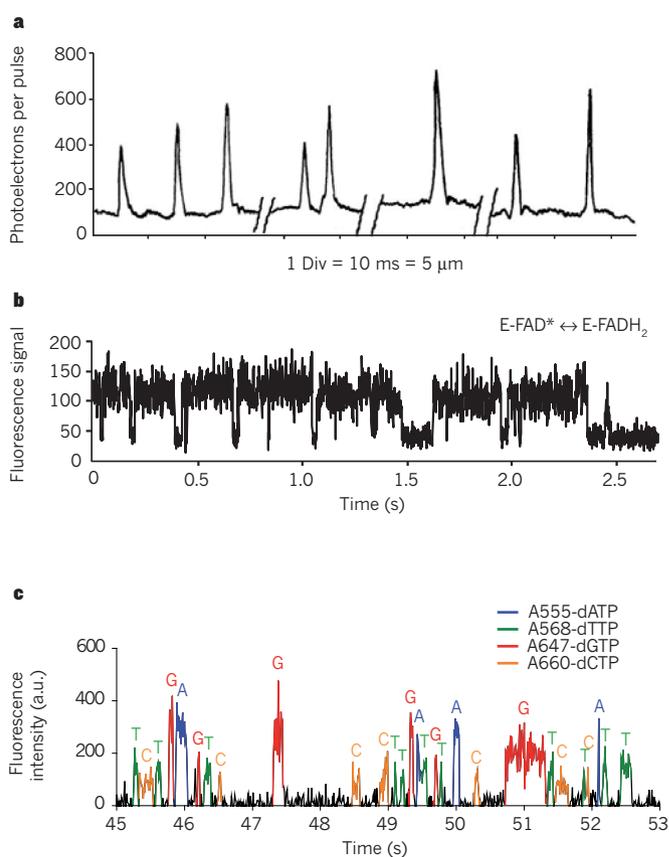


Figure 1 | Stochastic nature of single-molecule processes. **a**, Optical imaging of single protein molecules at room temperature. In his 1976 work, Hirschfeld demonstrated the detection of single protein molecules using a fluorescence microscope. A line scan of eight protein molecules was recorded. Div, division; adapted, with permission, from ref. 1. **b**, Stochastic turnovers of a single enzyme molecule. The fluorescence signal of a cholesterol oxidase molecule (E) shows stochastic switching between a fluorescent (oxidized flavin, FAD^{*}) and non-fluorescent (reduced flavin, FADH₂) state as enzymatic turnovers take place. Adapted from ref. 9. **c**, Single-molecule DNA sequencing. A single DNA polymerase is used to sequence DNA by incorporating fluorescently labelled nucleotides of four different colours. Although each incorporation happens stochastically with variable waiting times, the overall time for DNA replication, which is a sum of many sequential steps, is narrowly distributed. a.u., arbitrary units; adapted, with permission, from ref. 11.

one immobilized molecule in a diffraction-limited volume (less than 10 molecules within a bacterial cell). Detection by localization can be done by tethering on a membrane³⁴, or by specific or even transient nonspecific binding to DNA³⁵.

In cases in which the frame rate of the camera is insufficient to detect transient localization (<10 ms), a shorter pulse of laser excitation can be provided with each imaging frame^{33,35}, an idea borrowed from strobe photography. Detection by localization therefore allows single-molecule observations with millisecond time resolution.

The width of a single-molecule image is about half of the optical wavelength, owing to the diffraction limit. However, the accuracy of determining the centre position of a single isolated fluorescent protein can be as high as a few nanometres³⁶. To image more concentrated samples, higher spatial resolution can also be achieved by selectively observing only one molecule at a time using photoactivatable fluorescent proteins. This is the idea behind recent developments in single-molecule-based super-resolution imaging, such as stochastic optical reconstruction microscopy³⁷ and photoactivated localization microscopy^{38,39}, in which high-resolution images are reconstructed from many single-molecule images. Future applications of super-resolution techniques will probably change the way we view intracellular

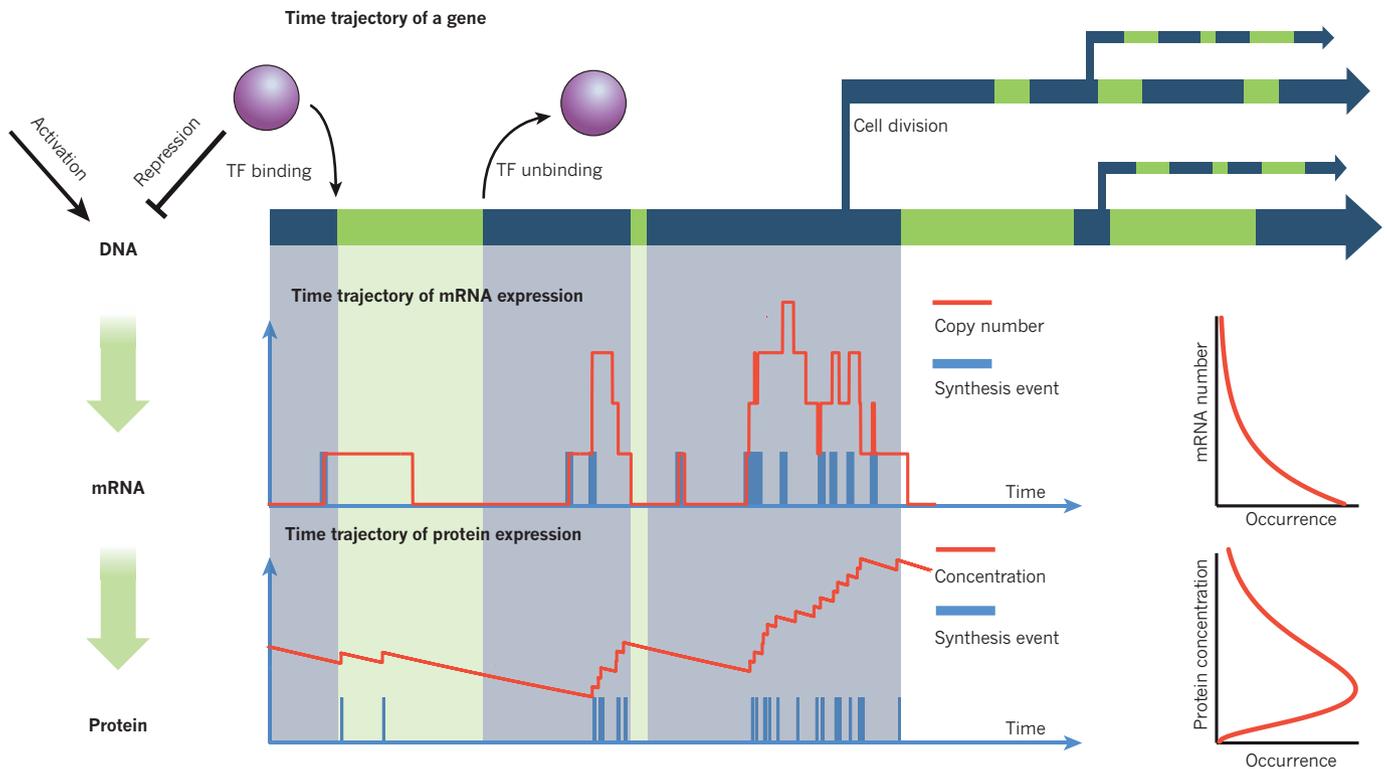


Figure 2 | Central dogma at the single-molecule level. In a living bacterial cell, there is usually one copy of a particular gene, which is regulated by transcription factors (TFs), and transcribed into mRNA and translated into protein. A rate-limiting event, such as transcription-factor binding to and unbinding from DNA,

in this single-molecule process results in stochasticity. The expression levels of mRNA (middle panel) and protein (bottom panel) show temporal fluctuations in a single-cell lineage. This gives rise to variations of mRNA and protein copy numbers among a population of cells at a particular time (right panels).

processes⁴⁰ such as gene expression. Single-fluorophore detection, as discussed above, remains a prerequisite for super-resolution imaging.

Transcription-factor dynamics

As the first step of gene expression, transcription factors must bind to or unbind from DNA in response to environmental signals. Because transcription factors interact with DNA at one location, gene expression is stochastic when the binding and unbinding of a transcription factor become rate limiting (Fig. 2). In the classic example of the *lac* operon, the transcription factor known as the *lac* repressor (LacI), which is expressed at fewer than five copies per cell³⁵, binds to or unbinds from operator sites to control transcription. With detection by localization, a single *lac* repressor fused to yellow fluorescent protein (YFP) can be visualized when bound to its operator in the *lac* operon³⁵. When the inducer isopropyl- β -D-thiogalactoside (IPTG) is added to the cell, localized fluorescent spots disappear as a result of LacI dissociation

(Fig. 4b). This living-cell assay allows single-molecule measurements of transcription-factor dissociation kinetics.

In addition, the binding kinetics can be measured. When IPTG is removed from the medium, the localized signal reappears, indicating the rebinding of LacI (Fig. 4c). This experiment allowed the first measurement of the time required for a LacI molecule to find a vacant operator site on DNA. It takes less than 360 s for one repressor to search for one specific binding site³⁵. This 360-s search time is a result of complex molecular processes. The protein–DNA search problem was extensively studied in the 1970s and 1980s^{41,42}. It was observed that the DNA-binding rate constant of transcription factors significantly exceeds that expected from the 3D diffusion limit for bimolecular binding⁴³. This observation led to the prevailing model of facilitated diffusion. For a transcription factor or any DNA-binding protein to find a target sequence on DNA, it first binds somewhere along the DNA nonspecifically and undergoes 1D diffusion in search of the target. If the target is not found, the

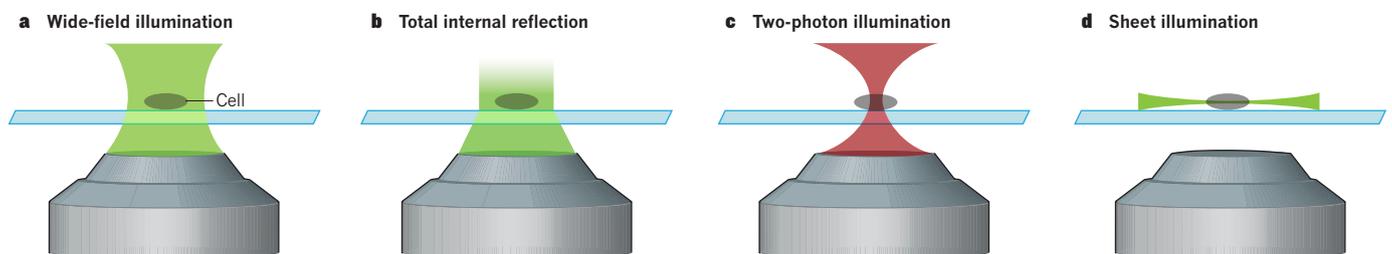


Figure 3 | Methods for imaging single molecules in living cells. Single-molecule fluorescence can be imaged using multiple laser illumination geometries that reduce the probe volume. **a**, In wide-field illumination, the entire cell is subject to laser exposure. For bacterial cells that have small volume, no further probe volume reduction is necessary. **b**, With total internal reflection, only the region within a few hundred nanometres of the coverslip

is illuminated. This method is often used to image single membrane proteins, but cannot detect molecules deep in the cells. **c**, Two-photon excitation suppresses out-of-focus background, but suffers from slower time resolution owing to the need for point scanning. **d**, Sheet illumination has reduced background, as well as increased time resolution, because it does not require point scanning.

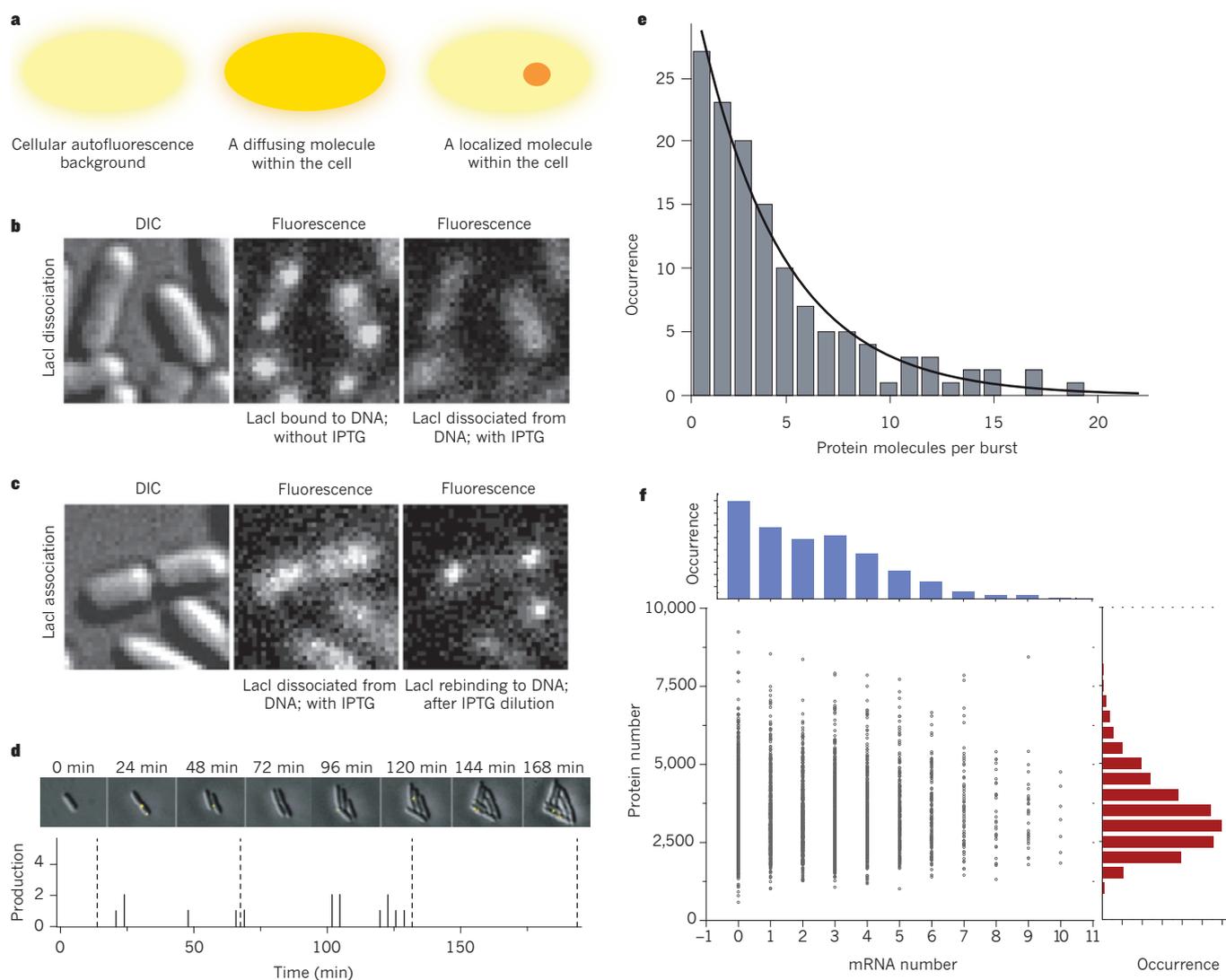


Figure 4 | Real-time measurements of gene expression with single-molecule sensitivity. **a**, Detection by localization. The cellular autofluorescence makes it difficult to detect a freely diffusing fluorescent protein. However, a localized single molecule can be imaged above the autofluorescence background. **b**, Detection of single transcription factors in living cells. A *lac* repressor (LacI) labelled with YFP can be imaged when bound to its operator site on DNA. The localized fluorescence disappears after dissociation caused by the inducer IPTG. DIC, differential interference contrast microscopy; adapted from ref. 35. **c**, Rebinding of LacI to the operator on dilution of IPTG, as evident from the reappearance of the fluorescence localization. The average rebinding time is 60 s, which can be explained by the facilitated diffusion model for a target search. Adapted from ref. 35. **d**, Real-time observation of protein synthesis under repressed

transcription factor dissociates from the DNA to avoid a long search time imposed by 1D diffusion. The 3D diffusion through the cytoplasm is much faster, allowing the transcription factor to reach distant segments of DNA quickly. This combined 1D and 3D search is repeated until the transcription factor finds the DNA segment containing the target sequence. With single-molecule experiments, one can probe these phenomena in real time and quantify the process.

In a series of single-molecule studies *in vitro*, 1D diffusion has been directly observed for fluorescently labelled transcription factors and other DNA-binding proteins along nonspecific DNA under a microscope^{44–49}. The observed 1D diffusion rate (of the order of $0.05 \mu\text{m}^2 \text{s}^{-1}$) is much slower than the 3D diffusion in a living cell ($\sim 3 \mu\text{m}^2 \text{s}^{-1}$) because the 1D diffusion of the transcription factor is

coupled to simultaneous rotation around the DNA, tracking the pitch of the DNA double helix^{50,51}. In the *in vitro* experiments, low salt concentrations were used to ensure long nonspecific residence times so that long trajectories of 1D diffusion could be recorded. In a living cell, high salt concentration shortens the residence time, but the diffusion constant often remains the same⁴⁶. Consequently, the number of bases inspected in each 1D search segment is reduced.

A key question is whether such facilitated diffusion occurs in living cells. Recent single-molecule experiments suggest that it does. During the search process, a transcription factor spends 90% of its time on nonspecific DNA, and the residence time of nonspecific binding is less than 5 ms (ref. 35). Given the 1D diffusion constant *in vitro*, the protein inspects ~ 100 base pairs (bp), which implies a 100-fold acceleration

of target search compared with the case with no 1D diffusion⁵². This observation is consistent with mounting evidence that the length of the DNA segment that a transcription factor inspects is shorter than 1,000 bp^{53–57}, the value estimated from early *in vitro* experiments⁴³. This 100-bp range indicates that for a 5×10^6 bp genome, a transcription factor must inspect $5 \times 10^6/100 = 5 \times 10^4$ segments before reaching the target site. Therefore, the total search time for one transcription factor in a cell is $\sim 5 \times 10^4 \times 5 \text{ ms} = 250 \text{ s}$, in close agreement with the measured search time³⁵.

The combination of different single-molecule approaches has resolved the search problem and led to a quantitative understanding of the facilitated diffusion of transcription factors in bacteria. Similar single-molecule experiments should be able to address the same search problem in mammalian cells, which is complicated by nucleosomes.

Gene expression in real time

Transcription-factor binding or unbinding leads to transcription and translation. Although the central dogma has been well established, real-time observation and quantitative description of transcription and translation in a single cell, at the single-molecule level, have only become possible in recent years. These studies have yielded unexpected observations of these fundamental processes in living cells^{34,58–62}.

We first discuss protein production, as it is better understood at the single-molecule level under repressed (non-induced) conditions. Under these conditions, single-molecule experiments have shown that proteins are synthesized in bursts³⁴, and that the characteristics of the bursts can be understood quantitatively at the molecular level. The stochastic production of individual molecules of a YFP-fused membrane protein has been monitored in real time in *Escherichia coli*³⁴ (Fig. 4d). Newly synthesized YFPs were visualized one by one as diffraction-limited spots through detection by localization, and they were purposely photobleached after being detected. A fast-maturing YFP, Venus⁶³, was used to achieve 7-min time resolution in the observation of translation. Using this approach, translational bursting from the *lac* operon under repressed conditions was observed³⁴. Each burst creates four proteins on average, at a frequency of about one burst per generation time (although not synchronized to the cell cycle). The number of bursts per cell cycle follows the Poisson distribution.

Because it was shown that each burst results from transcription of a single mRNA (generated owing to the occasional dissociation of the LacI repressor), the observed translational burst must therefore be due to several rounds of ribosomal initiation on the same transcript. This transcript is degraded by nucleases with a stochastic cellular lifetime that is exponentially distributed with a time constant of 1.5 min. The longer an mRNA lives, the more proteins it produces. Consequently, as theoretically predicted in the 1970s^{64–66}, the burst size is exponentially distributed (Fig. 4e). This observation of exponentially distributed protein copy numbers per burst was independently confirmed by another single-molecule assay using β -galactosidase activity as a reporter⁶². As we discuss later, such stochastic expression due to transcription-factor unbinding can be important in determining how a gene is induced in the presence of external stimuli⁶⁷.

Under repressed conditions in *E. coli*, the mRNA production is Poissonian. Under induced conditions, however, mRNA too is produced in bursts. One widely adopted method to detect single mRNA molecules in living cells uses the bacteriophage coat proteins (MS2) that stably bind to specific RNA sequences⁶⁸. To visualize single copies of mRNA, cell lines are engineered to express both MS2–green fluorescent protein (GFP) and mRNA containing several MS2-binding sites. First developed by the Singer group, this method allows real-time observation of transcript production, and is ideal for probing transcriptional dynamics in living cells by tracking and counting single mRNA–MS2–GFP complexes^{69,70}. A caveat is that the secondary structure associated with the binding sites and MS2 binding often interferes with the native mRNA degradation pathways⁷¹, preventing the profiling of endogenous mRNA expression levels.

When MS2-containing mRNA is expressed under fully induced

conditions, the production of transcripts is found to be intermittent⁵⁸. If transcript production were to have a single rate-limiting step, such as RNA polymerase binding or initiation, the waiting time between the birth of each mRNA would be exponentially distributed, and the copy-number distribution would be Poissonian (with a variance equal to the mean). Surprisingly, short bursts (average 6 min) of mRNA synthesis followed by long periods (average 37 min) of inactivity have been observed⁵⁸. The burst-like transcription is similar to that shown in Fig. 4d, even though there is no known transcription-factor binding or unbinding in this case. This burst-like transcription was also observed using fluorescence correlation spectroscopy on MS2-bound mRNA in *E. coli*⁵⁹, as well as in eukaryotic cells^{60,61}. Although the overall waiting time between each mRNA synthesis event is not exponentially distributed⁵⁸, the waiting times for transition between the active and the inactive states are. Accordingly, the copy-number distribution is super-Poissonian, meaning that the variance of the distribution is greater than the mean. In other words, the cell-to-cell variation is significantly greater than what would be expected from a single rate-limiting process.

This important finding pointed out that transcription from a supposedly constitutive promoter is not as simple as RNA polymerases transcribing with a constant flux. Rather, it is a much noisier process, and the origin of this noise is unknown. Possible candidates include the role of nucleoid-associated proteins that are analogous to eukaryotic histones, global fluctuations of chromosome supercoiling states and RNA polymerase availability. *In vivo* single-molecule approaches are poised to further reveal the workings of these fundamental processes.

Characterization of cell-to-cell variation

Under steady-state conditions, temporal fluctuations of gene expression in each cell lineage, as discussed in the previous section and Fig. 2, lead to variation in copy number in an isogenic population of cells. A typical copy-number distribution, which is often asymmetrical, is shown in Fig. 4f. A rigorous mathematical relationship between fluctuations in expression and the distribution of protein copy number in a population of cells has been lacking. A log-normal function has often been used as a convenient phenomenological fit, but it offers no physical insight.

For each gene, the dynamics of the central dogma can be described by two parameters — the burst frequency, a , which is the number of bursts per cell cycle; and the burst size, b , which is the average number of molecules produced per burst. Experimentally, a and b can be determined by single-cell trajectories, such as in Fig. 2. Alternatively, the fact that temporal fluctuations in a cell lineage are related to cell-to-cell variation of copy numbers suggests that a and b can also be inferred from a population of isogenic cells at a particular moment, as observed with a microscope or flow cytometer.

To find the relationship, we needed a governing equation for gene-expression dynamics. This is the chemical master equation, which was first used by Delbrück⁷² in 1940. In the late 1970s, the chemical master equation was applied to obtain protein copy-number distributions resulting from stochastic gene expression^{64,65}. It was not until a decade ago that this approach regained attention^{66,73,74}. Given the chemical kinetics scheme and rate constants connecting all the macromolecules involved in the central dogma, one can, in principle, solve the chemical master equation, which naturally yields time-dependent fluctuations. In practice, this can be simulated numerically using the Gillespie algorithm⁷⁵. Under certain conditions, analytical results can be obtained. For example, under steady-state conditions with uncorrelated and exponentially distributed bursts, the chemical master equation can be solved⁷⁶, and the protein copy-number distribution, $p(n)$, can be approximated as a gamma distribution when the copy number (n) is approximated as a continuous variable⁷⁷:

$$p(n) = n^{a-1} e^{-n/b} / b^a \Gamma(a)$$

The gamma distribution has two kinetic parameters — a and b , as defined earlier — providing a clear physical interpretation of the

copy-number distribution. This mathematical relationship allows extraction of intrinsic kinetic parameters (a and b) from fitting a gamma function to the measured copy-number distribution. At low expression levels, the values for a and b determined in this way are consistent with those derived from the single-cell trajectories^{34,62}. As discussed in the next section, the cell-to-cell variation at high expression levels is more complicated but remains well described by a gamma distribution.

Gene-expression profiling

The ability to image single molecules in bacteria has offered an opportunity to profile protein expression globally, at any abundance level. Pioneering work using a yeast GFP fusion library⁷⁸ surveyed the cell-to-cell variation of more than 2,500 genes under various growth conditions, yielding several important observations^{79,80}. First, the noise, or the variance divided by the mean squared, scales inversely with abundance. Second, the deviation of noise in a particular gene away from the global trend reflects the protein function and perhaps the underlying regulation. However, because single-molecule sensitivity in yeast cells had not been achieved at the time, 30% of the genes that were weakly expressed in the GFP library were undetectable.

To profile global variation at all expression levels, an *E. coli* YFP fusion library was constructed, and included more than 1,000 genes with expression levels ranging from 0.1 to 10^4 proteins per cell²¹. Of all the tagged proteins, approximately 99% of the copy-number distributions are well fit with the gamma distribution. About 50% of the proteins are expressed at an average level of fewer than ten molecules per cell, which argues for the necessity of single-molecule sensitivity in single-cell analyses.

Protein-expression noise has two distinct scaling properties relative to the mean. Below ten molecules per cell, the noise is inversely proportional to protein abundance. This scaling is the same as that observed in yeast, indicating that the noise from random birth and death of molecules, also known as intrinsic noise^{81,82}, dominates the expression variation for low-abundance proteins. By contrast, at abundances above ten molecules per cell, the noise reaches a plateau of 30% and does not decrease any further. This noise plateau is common, or 'extrinsic', to most high-abundance proteins, as the expression levels of different proteins have a large covariance from cell to cell. Notably, time-lapse movies have shown that the extrinsic noise fluctuates at a timescale much longer than the cell cycle, suggesting that a slow global-regulation process is at work⁸³.

At the transcriptional level, the same YFP library has been used to simultaneously survey mRNA and protein variation for 137 highly expressed genes²¹. Instead of labelling with MS2, which requires further cloning steps, mRNA was visualized using single-molecule fluorescence *in situ* hybridization (FISH)^{84,85} in fixed cells. Unlike conventional approaches that use several hybridization probes against the mRNA, the YFP mRNA was targeted using a universal singly labelled FISH probe optimized for both hybridization efficiency towards its targets and specificity against off-targets. It was found that, even for highly expressed genes, the average mRNA copy number is fewer than five per cell. Among a population of genetically identical cells, every mRNA species has a distribution that is broader than a Poisson distribution (Fig. 4f), which is related to the transcriptional bursts observed in the real-time experiments and suggests that this is a general phenomenon for most genes.

The simultaneous profiling of mRNA and protein²¹ revealed that the mRNA and protein copy numbers of a single cell for any given gene are uncorrelated; that is, a cell that has more mRNA molecules than average does not necessarily have more proteins (Fig. 4f). This perhaps counter-intuitive result can be explained by the fact that mRNA has a much shorter lifetime than protein in bacteria¹⁹. This finding argues for the necessity of single-cell proteomics analyses, and offers a warning for interpretations of single-cell transcriptome data, at least for bacteria. A mammalian cell, by contrast, has comparable mRNA and protein lifetimes, and hence is expected to have more-correlated mRNA and protein levels than a bacterial cell.

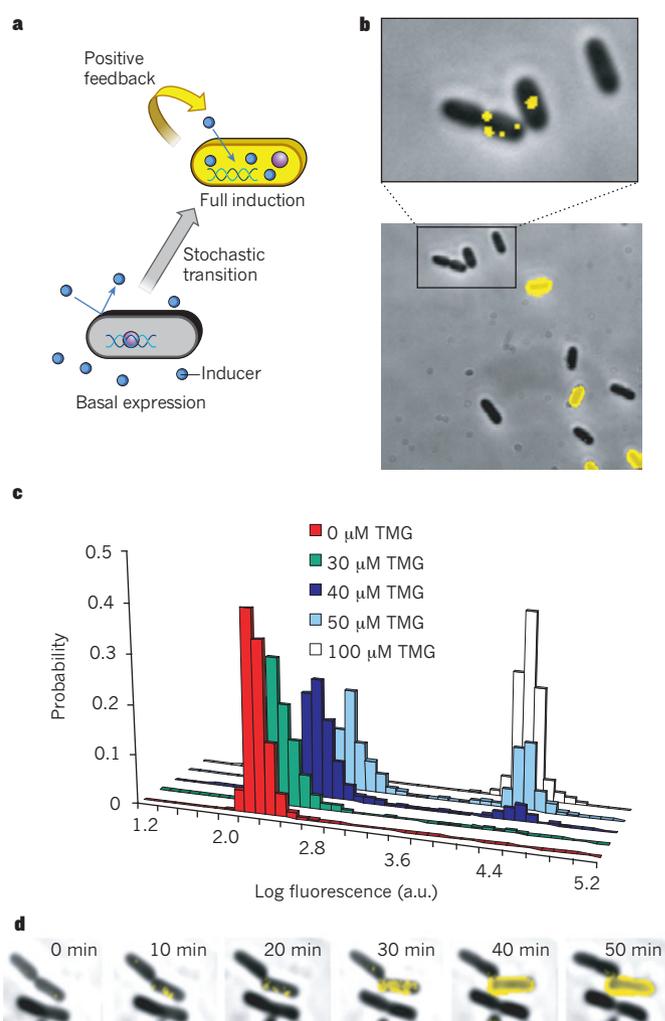


Figure 5 | Phenotype switching due to a single-molecule event. **a**, Bistability of the *lac* operon. The positive feedback by the normally repressed Lac permease (LacY, labelled with YFP) results in bimodal distribution at an intermediate inducer concentration, with two distinct phenotypes: strongly or weakly fluorescent. **b**, Fluorescence-microscope images show two phenotypes. The copy number of LacY in uninduced cells ranges from 0 to 10 molecules per cell, suggesting that one molecule of LacY is not enough to trigger the positive feedback. **c**, Bimodal distribution of LacY expression for isogenic cells at intermediate concentrations of an inducer (TMG, a lactose analogue). **d**, Time-lapse images capture the transition of a cell from one phenotype to another. A large expression burst of LacY (~300 molecules) is necessary to trigger the switching, which results from the complete dissociation of a single transcription factor, LacI, from DNA. This experiment shows that a low-probability, single-molecule stochastic event can determine cell fate. Adapted from ref. 67.

Gene regulation and phenotypic switching

How cells with identical genomes have different phenotypes is an interesting question. Phenotypes are the physical, chemical and physiological states of the cell as related to function, determined by both the genome and environment. Given the ubiquitous and substantial noise described earlier, it is evident that the phenotype of a cell cannot be solely defined by its transcriptome and proteome. Cells can tolerate rather large noise in protein and mRNA abundance while tightly maintaining their phenotypes. A compelling question is what molecular actions dictate the transition between phenotypes.

In some cases, the cell phenotype can be clearly defined when there are bimodal or multimodal distributions of proteins, in contrast to the unimodal copy-number distribution that is most often observed²¹. As shown in Fig. 5b, a population of isogenic *E. coli* cells, in which

Lac permease is labelled with YFP, shows bistability. The *lac* operon in *E. coli*, consisting of *lacZ*, *lacY* and *lacA* genes, is normally repressed by the *lac* transcription-factor repressor (LacI) in the absence of an inducer (Fig. 5a). When the inducer is present, it inactivates LacI and triggers expression of the *lac* operon⁸⁶. The synthesis of the permease increases the inducer influx, which inactivates more LacI, creating a positive feedback on permease expression⁸⁷. Without an inducer, no cells are induced, whereas with high inducer concentrations, all cells are induced. At moderate inducer concentrations, only a fraction of the cells are induced (Fig. 5c). This bistability is controlled by the positive feedback of the *lac* operon⁸⁸.

Bistability is commonly exploited by bacteria to generate alternative phenotypes⁸⁹, such as persistence against antibiotics⁹⁰, lysis or lysogeny after phage infection⁹¹ and induction of the *lac* operon in *E. coli*⁸⁷. Although much is known about the genetic switches, what drives the transition between two phenotypic states is unclear in many cases. How does a single cell make a decision about which phenotype to choose? With single-molecule imaging, uninduced *E. coli* cells have been shown to contain 0–10 copies of the permease enzyme, which is below the threshold for positive feedback (more than 300 molecules per cell)⁶⁷. Transition to the fully induced state therefore requires a large burst of protein synthesis (Fig. 5d).

The transcription factor controlling permease synthesis, LacI, is a tetramer that binds to two DNA-binding sites, creating a DNA loop. Partial dissociation of LacI and rapid rebinding to DNA result in a single copy of mRNA and a small burst of permease, as was observed in the aforementioned real-time studies of the repressed *lac* promoters. When the repressor completely dissociates from both operators on DNA, a large burst of permease arises, because it takes a few minutes for the repressor to rebind³⁵. Indeed, bistability was eliminated in strains without DNA looping⁶⁷. It is the stochastic single-molecule event of complete repressor dissociation from DNA that triggers the cell's phenotypic switching.

Looking forward

We have shown that in the case of the *lac* operon, the workings of the genetic switch can be quantitatively understood at the molecular level. This is an example of low probability, stochastic events of a single molecule having important biological consequences. Another simple example is point mutations in the course of evolution.

It is well recognized that such stochastic events are connected to cell-fate determination in other systems⁹². For example, there is considerable evidence that bacterial persistence against antibiotics is a stochastic process involving gene expression⁹⁰. Persisters are not drug resistant but are drug tolerant. Drug resistance is related to a changing genome, whereas persisters have identical genomes, but different phenotypes. The phenomenon exists for many bacterial species and antibiotics. The molecular mechanism behind persistence is largely unknown, partly because the tools are not available. Understanding the molecular mechanism of persistence may be crucial to drug development, especially for diseases such as tuberculosis, caused by the bacterium *Mycobacterium tuberculosis*, which kills almost 2 million people every year worldwide. Single-cell gene-expression profiling may shed light on the mechanism of persistence.

Similarly, the reprogramming of somatic cells into induced pluripotent stem cells in the presence of certain transcription factors is also stochastic⁹³. There are no elite cells, and every cell has a certain probability of being reprogrammed in the presence of some transcription factors, which is analogous to stochastic switching in the *E. coli lac* operon at low inducer concentrations. Yet, unlike the *lac* operon, the molecular mechanism is unknown. Extension of single-molecule approaches to mammalian cells and stem cells will allow real-time monitoring over long periods so that low-probability events with considerable biological consequences can be observed directly. We anticipate that the single-molecule approaches summarized in this Review will lead to more biological discoveries for many years to come. ■

- Hirschfeld, T. Optical microscopic observation of single small molecules. *Appl. Opt.* **15**, 2965–2966 (1976).
This paper presents the first single-molecule fluorescence imaging at room temperature, and the approach, which reduces the detection volume to enhance signal-to-background ratio, is widely used today *in vitro* and in living cells.
- Shera, E. B., Seitzinger, N. K., Davis, L. M., Keller, R. A. & Soper, S. A. Detection of single fluorescent molecules. *Chem. Phys. Lett.* **174**, 553–557 (1990).
- Betzig, E. & Chichester, R. J. Single molecules observed by near-field scanning optical microscopy. *Science* **262**, 1422–1425 (1993).
- Funatsu, T., Harada, Y., Tokunaga, M., Saito, K. & Yanagida, T. Imaging of single fluorescent molecules and individual ATP turnovers by single myosin molecules in aqueous solution. *Nature* **374**, 555–559 (1995).
- Schmidt, T., Schutz, G. J., Baumgartner, W., Gruber, H. J. & Schindler, H. Characterization of photophysics and mobility of single molecules in a fluid lipid-membrane. *J. Phys. Chem.* **99**, 17662–17668 (1995).
- Xie, X. S. & Trautman, J. K. Optical studies of single molecules at room temperature. *Annu. Rev. Phys. Chem.* **49**, 441–480 (1998).
- Moerner, W. E. & Orrit, M. Illuminating single molecules in condensed matter. *Science* **283**, 1670–1676 (1999).
- Ha, T. *et al.* Single-molecule fluorescence spectroscopy of enzyme conformational dynamics and cleavage mechanism. *Proc. Natl Acad. Sci. USA* **96**, 893–898 (1999).
- Lu, H. P., Xun, L. & Xie, X. S. Single-molecule enzymatic dynamics. *Science* **282**, 1877–1882 (1998).
This article reports real-time observation and statistical analyses of stochastic enzymatic turnover and shows that on a single-molecule basis, k_{cat} is not a constant.
- Hamill, O. P., Marty, A., Neher, E., Sakmann, B. & Sigworth, F. J. Improved patch-clamp techniques for high-resolution current recording from cells and cell-free membrane patches. *Pflügers Arch.* **391**, 85–100 (1981).
- Eid, J. *et al.* Real-time DNA sequencing from single polymerase molecules. *Science* **323**, 133–138 (2009).
This paper reports real-time sequencing of DNA using a single DNA polymerase molecule, a compelling application of single-molecule enzymology in biotechnology.
- Bouche, J. P. Physical map of a 470 x 10³ base-pair region flanking the terminus of DNA replication in the *Escherichia coli* K12 genome. *J. Mol. Biol.* **154**, 1–20 (1982).
- Bremer, H. A stochastic process determines the time at which cell division begins in *Escherichia coli*. *J. Theor. Biol.* **118**, 351–365 (1986).
- Wang, M. D. *et al.* Force and velocity measured for single molecules of RNA polymerase. *Science* **282**, 902–907 (1998).
- Blanchard, S. C., Kim, H. D., Gonzalez, R. L. Jr, Puglisi, J. D. & Chu, S. tRNA dynamics on the ribosome during translation. *Proc. Natl Acad. Sci. USA* **101**, 12893–12898 (2004).
- Kapanidis, A. N. *et al.* Initial transcription by RNA polymerase proceeds through a DNA-scrunching mechanism. *Science* **314**, 1144–1147 (2006).
- Wen, J. D. *et al.* Following translation by single ribosomes one codon at a time. *Nature* **452**, 598–603 (2008).
- Cornish, P. V., Ermolenko, D. N., Noller, H. F. & Ha, T. Spontaneous intersubunit rotation in single ribosomes. *Mol. Cell* **30**, 578–588 (2008).
- Bernstein, J. A., Khodursky, A. B., Lin, P. H., Lin-Chao, S. & Cohen, S. N. Global analysis of mRNA decay and abundance in *Escherichia coli* at single-gene resolution using two-color fluorescent DNA microarrays. *Proc. Natl Acad. Sci. USA* **99**, 9697–9702 (2002).
- Ishihama, Y. *et al.* Protein abundance profiling of the *Escherichia coli* cytosol. *BMC Genomics* **9**, 102 (2008).
- Taniguchi, Y. *et al.* Quantifying *E. coli* proteome and transcriptome with single-molecule sensitivity in single cells. *Science* **329**, 533–538 (2010).
This article profiles the transcriptome and proteome with single-molecule sensitivity in single cells, and shows that the protein copy-number distribution of most genes can be well fit with gamma distribution.
- Xie, X. S., Choi, P. J., Li, G. W., Lee, N. K. & Lia, G. Single-molecule approach to molecular biology in living bacterial cells. *Annu. Rev. Biophys.* **37**, 417–444 (2008).
- Giepmans, B. N., Adams, S. R., Ellisman, M. H. & Tsien, R. Y. The fluorescent toolbox for assessing protein location and function. *Science* **312**, 217–224 (2006).
- Andersson, H., Baechli, T., Hoechl, M. & Richter, C. Autofluorescence of living cells. *J. Microsc.* **191**, 1–7 (1998).
- Sako, Y., Minoghchi, S. & Yanagida, T. Single-molecule imaging of EGFR signalling on the surface of living cells. *Nature Cell Biol.* **2**, 168–172 (2000).
- Iino, R., Koyama, I. & Kusumi, A. Single molecule imaging of green fluorescent proteins in living cells: E-cadherin forms oligomers on the free cell surface. *Biophys. J.* **80**, 2667–2677 (2001).
- Wilson, T. *Confocal Microscopy* (Academic, 1990).
- Denk, W., Strickler, J. H. & Webb, W. W. Two-photon laser scanning fluorescence microscopy. *Science* **248**, 73–76 (1990).
- Sanchez, E. J., Novotny, L., Holtom, G. R. & Xie, X. S. Room-temperature fluorescence imaging and spectroscopy of single molecules by two-photon excitation. *J. Phys. Chem. A* **101**, 7019–7023 (1997).
- Fuchs, E., Jaffe, J., Long, R. & Azam, F. Thin laser light sheet microscope for microbial oceanography. *Opt. Express* **10**, 145–154 (2002).
- Ritter, J. G., Veith, R., Veenendaal, A., Siebrasse, J. P. & Kubitschek, U. Light sheet microscopy for single molecule tracking in living tissue. *PLoS ONE* **5**, e11639 (2010).

32. Elowitz, M. B., Surette, M. G., Wolf, P. E., Stock, J. B. & Leibler, S. Protein mobility in the cytoplasm of *Escherichia coli*. *J. Bacteriol.* **181**, 197–203 (1999).
33. Xie, X. S., Yu, J. & Yang, W. Y. Living cells as test tubes. *Science* **312**, 228–230 (2006).
34. Yu, J., Xiao, J., Ren, X., Lao, K. & Xie, X. S. Probing gene expression in live cells, one protein molecule at a time. *Science* **311**, 1600–1603 (2006).
This article monitors the real-time production of individual proteins by imaging newly synthesized YFP molecules, demonstrating translational bursts from a repressed promoter.
35. Elf, J., Li, G. W. & Xie, X. S. Probing transcription factor dynamics at the single-molecule level in a living cell. *Science* **316**, 1191–1194 (2007).
This article probes specific and nonspecific binding of a transcription factor to DNA, and measures the search time for a transcription factor to reach its target site in a living bacterial cell.
36. Thompson, R. E., Larson, D. R. & Webb, W. W. Precise nanometer localization analysis for individual fluorescent probes. *Biophys. J.* **82**, 2775–2783 (2002).
37. Rust, M. J., Bates, M. & Zhuang, X. Sub-diffraction-limit imaging by stochastic optical reconstruction microscopy (STORM). *Nature Methods* **3**, 793–795 (2006).
38. Betzig, E. *et al.* Imaging intracellular fluorescent proteins at nanometer resolution. *Science* **313**, 1642–1645 (2006).
39. Hess, S. T., Girirajan, T. P. & Mason, M. D. Ultra-high resolution imaging by fluorescence photoactivation localization microscopy. *Biophys. J.* **91**, 4258–4272 (2006).
40. Hell, S. W. Far-field optical nanoscopy. *Science* **316**, 1153–1158 (2007).
41. Richter, P. H. & Eigen, M. Diffusion controlled reaction rates in spheroidal geometry: application to repressor–operator association and membrane bound enzymes. *Biophys. Chem.* **2**, 255–263 (1974).
42. Berg, O. G., Winter, R. B. & von Hippel, P. H. Diffusion-driven mechanisms of protein translocation on nucleic acids. 1. Models and theory. *Biochemistry* **20**, 6929–6948 (1981).
43. Riggs, A. D., Bourgeois, S. & Cohn, M. The *lac* repressor–operator interaction. 3. Kinetic studies. *J. Mol. Biol.* **53**, 401–417 (1970).
44. Kabata, H. *et al.* Visualization of single molecules of RNA polymerase sliding along DNA. *Science* **262**, 1561–1563 (1993).
45. Harada, Y. *et al.* Single-molecule imaging of RNA polymerase–DNA interactions in real time. *Biophys. J.* **76**, 709–715 (1999).
46. Blainey, P. C., van Oijen, A. M., Banerjee, A., Verdine, G. L. & Xie, X. S. A base-excision DNA-repair protein finds intrahelical lesion bases by fast sliding in contact with DNA. *Proc. Natl Acad. Sci. USA* **103**, 5752–5757 (2006).
47. Granell, A., Yeykal, C. C., Robertson, R. B. & Greene, E. C. Long-distance lateral diffusion of human Rad51 on double-stranded DNA. *Proc. Natl Acad. Sci. USA* **103**, 1221–1226 (2006).
48. Tafvizi, A., Huang, F., Fersht, A. R., Mirny, L. A. & van Oijen, A. M. Tumor suppressor p53 slides on DNA with low friction and high stability. *Biophys. J.* **95**, L01–L03 (2008).
49. Kim, J. H. & Larson, R. G. Single-molecule analysis of 1D diffusion and transcription elongation of T7 RNA polymerase along individual stretched DNA molecules. *Nucleic Acids Res.* **35**, 3848–3858 (2007).
50. Schurr, J. M. The one-dimensional diffusion coefficient of proteins absorbed on DNA. Hydrodynamic considerations. *Biophys. Chem.* **9**, 413–414 (1979).
51. Blainey, P. C. *et al.* Nonspecifically bound proteins spin while diffusing along DNA. *Nature Struct. Mol. Biol.* **16**, 1224–1229 (2009).
52. Li, G. W., Berg, O. G. & Elf, J. Effects of macromolecular crowding and DNA looping on gene regulation kinetics. *Nature Phys.* **5**, 294–297 (2009).
53. Stanford, N. P., Szczelkun, M. D., Marko, J. F. & Halford, S. E. One- and three-dimensional pathways for proteins to reach specific DNA sites. *EMBO J.* **19**, 6546–6557 (2000).
54. Winter, R. B., Berg, O. G. & von Hippel, P. H. Diffusion-driven mechanisms of protein translocation on nucleic acids. 3. The *Escherichia coli lac* repressor–operator interaction: kinetic measurements and conclusions. *Biochemistry* **20**, 6961–6977 (1981).
55. Gowers, D. M. & Halford, S. E. Protein motion from non-specific to specific DNA by three-dimensional routes aided by supercoiling. *EMBO J.* **22**, 1410–1418 (2003).
56. Bonnet, I. *et al.* Sliding and jumping of single EcoRV restriction enzymes on non-cognate DNA. *Nucleic Acids Res.* **36**, 4118–4127 (2008).
57. Porecha, R. H. & Stivers, J. T. Uracil DNA glycosylase uses DNA hopping and short-range sliding to trap extrahelical uracils. *Proc. Natl Acad. Sci. USA* **105**, 10791–10796 (2008).
58. Golding, I., Paulsson, J., Zawilski, S. M. & Cox, E. C. Real-time kinetics of gene activity in individual bacteria. *Cell* **123**, 1025–1036 (2005).
This article uses MS2–GFP to follow the production of individual mRNA molecules in real time in bacterial cells.
59. Le, T. T. *et al.* Real-time RNA profiling within a single bacterium. *Proc. Natl Acad. Sci. USA* **102**, 9160–9164 (2005).
60. Chubb, J. R., Trcek, S., Shenoy, S. M. & Singer, R. H. Transcriptional pulsing of a developmental gene. *Curr. Biol.* **16**, 1018–1025 (2006).
61. Raj, A., Peskin, C. S., Tranchina, D., Vargas, D. Y. & Tyagi, S. Stochastic mRNA synthesis in mammalian cells. *PLoS Biol.* **4**, e309 (2006).
62. Cai, L., Friedman, N. & Xie, X. S. Stochastic protein expression in individual cells at the single molecule level. *Nature* **440**, 358–362 (2006).
63. Nagai, T. *et al.* A variant of yellow fluorescent protein with fast and efficient maturation for cell-biological applications. *Nature Biotechnol.* **20**, 87–90 (2002).
64. Berg, O. G. A model for the statistical fluctuations of protein numbers in a microbial population. *J. Theor. Biol.* **71**, 587–603 (1978).
65. Rigney, D. R. Stochastic-model of constitutive protein levels in growing and dividing bacterial cells. *J. Theor. Biol.* **76**, 453–480 (1979).
66. McAdams, H. H. & Arkin, A. Stochastic mechanisms in gene expression. *Proc. Natl Acad. Sci. USA* **94**, 814–819 (1997).
67. Choi, P. J., Cai, L., Frieda, K. & Xie, X. S. A stochastic single-molecule event triggers phenotype switching of a bacterial cell. *Science* **322**, 442–446 (2008).
This article investigates the triggering mechanism of the *lac* operon bistable switch and shows that the dissociation of a single *lac* repressor is responsible for the phenotype switch to the induced state.
68. Tyagi, S. Imaging intracellular RNA distribution and dynamics in living cells. *Nature Methods* **6**, 331–338 (2009).
69. Bertrand, E. *et al.* Localization of *ASH1* mRNA particles in living yeast. *Mol. Cell* **2**, 437–445 (1998).
This study develops an approach to image individual mRNA molecules in living cells, using fluorescent protein-fused MS2 proteins that bind to an engineered mRNA sequence.
70. Beach, D. L., Salmon, E. D. & Bloom, K. Localization and anchoring of mRNA in budding yeast. *Curr. Biol.* **9**, 569–578 (1999).
71. Johansson, H. E. *et al.* A thermodynamic analysis of the sequence-specific binding of RNA by bacteriophage MS2 coat protein. *Proc. Natl Acad. Sci. USA* **95**, 9244–9249 (1998).
72. Delbrück, M. Statistical fluctuations in autocatalytic reactions. *J. Chem. Phys.* **8**, 120–140 (1940).
73. Paulsson, J. Summing up the noise in gene networks. *Nature* **427**, 415–418 (2004).
74. Shahrezaei, V. & Swain, P. S. Analytical distributions for stochastic gene expression. *Proc. Natl Acad. Sci. USA* **105**, 17256–17261 (2008).
75. Gillespie, D. T. A general method for numerically simulating the stochastic time evolution of coupled chemical reactions. *J. Comput. Phys.* **22**, 403–434 (1976).
76. Paulsson, J. & Ehrenberg, M. Random signal fluctuations can reduce random fluctuations in regulated components of chemical regulatory networks. *Phys. Rev. Lett.* **84**, 5447–5450 (2000).
77. Friedman, N., Cai, L. & Xie, X. S. Linking stochastic dynamics to population distribution: an analytical framework of gene expression. *Phys. Rev. Lett.* **97**, 168302 (2006).
This article derives gamma distribution of protein copy numbers in a model with burst-like gene expression; the distribution is in agreement with experimental observations in reference 62.
78. Huh, W. K. *et al.* Global analysis of protein localization in budding yeast. *Nature* **425**, 686–691 (2003).
79. Newman, J. R. *et al.* Single-cell proteomic analysis of *S. cerevisiae* reveals the architecture of biological noise. *Nature* **441**, 840–846 (2006).
80. Bar-Even, A. *et al.* Noise in protein expression scales with natural protein abundance. *Nature Genet.* **38**, 636–643 (2006).
81. Swain, P. S., Elowitz, M. B. & Siggia, E. D. Intrinsic and extrinsic contributions to stochasticity in gene expression. *Proc. Natl Acad. Sci. USA* **99**, 12795–12800 (2002).
82. Thattai, M. & van Oudenaarden, A. Intrinsic noise in gene regulatory networks. *Proc. Natl Acad. Sci. USA* **98**, 8614–8619 (2001).
83. Elowitz, M. B., Levine, A. J., Siggia, E. D. & Swain, P. S. Stochastic gene expression in a single cell. *Science* **297**, 1183–1186 (2002).
84. Femino, A. M., Fay, F. S., Fogarty, K. & Singer, R. H. Visualization of single RNA transcripts *in situ*. *Science* **280**, 585–590 (1998).
85. Maamar, H., Raj, A. & Dubnau, D. Noise in gene expression determines cell fate in *Bacillus subtilis*. *Science* **317**, 526–529 (2007).
This article used single-molecule FISH to show that the noise in the expression of a transcription factor determines whether a *Bacillus subtilis* cell becomes competent.
86. Jacob, F. & Monod, J. Genetic regulatory mechanisms in the synthesis of proteins. *J. Mol. Biol.* **3**, 318–356 (1961).
87. Ozbudak, E. M., Thattai, M., Lim, H. N., Shraiman, B. I. & Van Oudenaarden, A. Multistability in the lactose utilization network of *Escherichia coli*. *Nature* **427**, 737–740 (2004).
88. Novick, A. & Weiner, M. Enzyme induction as an all-or-none phenomenon. *Proc. Natl Acad. Sci. USA* **43**, 553–566 (1957).
89. Dubnau, D. & Losick, R. Bistability in bacteria. *Mol. Microbiol.* **61**, 564–572 (2006).
90. Balaban, N. Q., Merrin, J., Chait, R., Kowalik, L. & Leibler, S. Bacterial persistence as a phenotypic switch. *Science* **305**, 1622–1625 (2004).
91. Ptashne, M. *A Genetic Switch* 3rd edn (Cold Spring Harbor Laboratory Press, 2004).
92. Losick, R. & Desplan, C. Stochasticity and cell fate. *Science* **320**, 65–68 (2008).
93. Hanna, J. *et al.* Direct cell reprogramming is a stochastic process amenable to acceleration. *Nature* **462**, 595–601 (2009).

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