‘Big data’ in physics education: discovering the stick-slip effect through a high sample rate

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Abstract
With the availability of educational digital data acquisition systems, it has also become possible in physics education to generate ‘big’ data sets by (a) measuring multiple variables simultaneously, (b) increasing the sample rate, (c) extending the measurement duration, or (d) choosing a combination among these three options. In the context of this paper, we will use a simple acceleration experiment to show that a higher sample rate, resulting in a larger data set, quantitatively reveals the stick-slip effect. For this purpose, two variables are measured simultaneously, first with a low and then with a high sample rate. The purpose of this paper is to illustrate that dealing with ‘big’ data sets can add value to experimentation in physics labs by dealing with data sets that more accurately describe observations.

Keywords: argumentation from data, data acquisition, sample rate, stick-slip effect

1. Introduction
The fundamental idea of experimentation is to link theoretically developed models and ideas with the domain of real objects and observable entities, by generating empirical evidence from measurement data and observations [1, 2]. This evidence can be used, among other ways, in an argumentative discourse to support a scientific claim [3, 4] (e.g. by using this evidence to justify hypotheses [5, 6]). Accordingly, due to the importance of ‘Analyzing and interpreting data’ and ‘Engaging in argument from evidence’ in the scientific endeavour, these processes are also formulated in the educational standards of various countries [7].

Currently digital measurement acquisition methods are used almost exclusively in physics research, since analog measurement methods are not feasible due to the complex experimental setups required. In contrast to measurement...
data acquired ‘by hand’, measurement data acquired by digital acquisition methods are usually characterised by (a) a high sample rate, (b) a long measurement duration, (c) the simultaneous measurement of several variables or (d) a combination of the previously mentioned three characteristics [8]. Regardless of whether analog or digital measurement methods are used, increasing any of these four characteristics inevitably leads to a larger amount of measurement data. While the sheer increase of measurement data does not immediately have the same dimensions, scale and significance as does Big Data, as the term is used in the tech world, we still refer to Big Data as ‘big data’, since data yielded by the use of digital measurement methods also require special methods for evaluation. We distinguish between ‘big data’ and ‘small data’ in the physics education context in that the measurement data can no longer be recorded with analog methods (e.g. manual reading of analog measuring instruments and their entry in laboratory books) or processed (e.g. manual handling of the measured data, such as the transfer of the measured data from a tabular into a graphical form of presentation), and therefore, digital data acquisition systems and evaluation methods are required to collect and process these amounts of measurement data.

While digital data acquisition systems for education have been around for more than 30 years, and recent research provides various examples of how to use these tools in physics education (e.g. [9–12]), we argue that the didactic potential of digital data acquisition systems has not yet been considered in physics education research. However, what exactly is the didactic potential of ‘big data’ for physics education, and why should we handle ‘big data’ in physics education? On the one hand, digitisation-related competencies can certainly be addressed, since a manual evaluation of ‘big data’ with pencil and paper, is not possible and digital evaluation tools such as Excel [13], GeoGebra [14] or MakerPlot [15] have to be used for data preparation, presentation and evaluation. On the other hand, and in our opinion even more relevant, is the fact that increasing either (a) velocity (e.g. sample rate of a digital measurement), (b) volume (measurement duration) or (c) the number of variables in a measurement increases and/or alters the amount of evidence that can be generated from a data set. Seeing experimentation as a process of linking data and observations as evidence with claims shows the potential of ‘big data’ in physics education: using digital data acquisition systems can make other, previously inaccessible, physical phenomena can be empirically assessed and used in the teaching of physics!

It is for this reason that we will exemplarily demonstrate, how ‘big data’ can be used to detect the motion of a body at a higher resolution than measuring ‘by hand’ (e.g. altering the sample rate, taking more measurements per time interval) to quantitatively obtain data about a physical phenomenon that would otherwise remain hidden (e.g. when measured at a smaller sample rate). However, we want to stress that this paper only focuses on one of the three aspects of ‘big data’, namely the velocity of taking measurements, and not by generating big data by increasing the number of variables and/or the measurement time. We do this in view of the fact that we want to show that changes in motion and accelerating force can be resolved more precisely by a high sample rate.

Against this background, this paper uses a simple acceleration experiment to show how a high sample rate can uncover the stick-slip effect, a well-known phenomenon responsible for squeaky doors and rattling windshield wipers.

2. Discovering the stick-slip effect through a high sample rate

While analog measurement methods can only roughly resolve the accelerating forces and motion of bodies due to a very low data acquisition rate, the use of digital acquisition methods can resolve both variables at a much higher measurement rate. These low sample rates can become a problem when learners observe a constant alternation of accelerating and decelerating bodies (stick-slip effect) but do not see this effect mapped into quantitative distance measurement data of the body due to the low sample rate. In this case, however, where observations (a stop and go motion) and measurement data do not lead to the same conclusion (namely that a periodic change in the resulting acceleration force leads to a stop and go motion, which characterises the stick-slip
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Figure 1. Frictional force $F_f(t)$ and distance $d(t)$ travelled of body $K$ for (a) different ($\mu_s > \mu_k$) and (b) strongly different ($\mu_s \gg \mu_k$) friction constants: area 1 shows the condition in which no drag force $F_D$ acts on body $K$ to be accelerated. Area 2 shows the condition in which a drag force $F_D$, which increases linearly with time, acts on body $K$. However, this force is not large enough to overcome the maximum static frictional force $F_{sF,\text{max}}$ once, so that body $K$ moves. Area 3 shows the condition in which body $K$ is moving (after the drag force $F_D$ overcomes once the maximum static frictional force $F_{sF,\text{max}}$) and a constant kinetic frictional force $F_{kF}$ acts on body $K$. Area 4 (as well as area 3) shows the slip state, in which body $K$ moves, and Area 5 shows the stick state, in which body $K$ adheres to the friction surface. The phases of areas 4 and 5 alternate with each other and represent the stick-slip effect.

Note: For better clarity and comparability, the ratio of the two friction coefficients $\mu_s$ and $\mu_k$ is shown as equal.

2.1. Theoretical background

On a body $K$ lying on a plane surface, the weight $F_G = m \cdot g$ and a normal force $F_N$ act independently from the state of motion. Only if an external force acts on body $K$ as a dragging force $F_D$, a friction force $F_f$ which is of the same magnitude but in the opposite direction of the drag force $F_D$ also acts on body $K$ at the same time. Figure 1 shows the friction force acting on a body $K$ (a) when no drag force $F_D$ is acting (area 1) and (b) when a drag force $F_D$, which increases linearly over time, is acting (area 2).

The frictional force $F_f$ depends on the magnitude of the acting normal force $F_N$ and on acting recoil forces arising from surface properties of the friction surface and body $K$ (for the sake of simplicity, we refrain from also reporting on acting adhesion and cohesion forces). The recoil forces result from the unevenness of the surfaces of body $K$ and the friction surface, which build mechanical connections [16].

To accelerate body $K$, a drag force $F_D$ must act on body $K$, which overcomes the maximum static friction force $F_{sF,\text{max}} = \mu_s F_N$ (see areas 1 and 2 in figure 1). $\mu_s$ is a material-dependent friction constant for the case when body $K$ is not in motion. Only then, when the drag force $F_D$ overcomes the maximum static friction force $F_{sF,\text{max}} < F_D$, is body $K$ in motion and a kinetic effect), the resulting controversial situation could lead to learners rejecting physical laws and/or finding them not persuasive. Digital data acquisition methods can help here, since on the one hand, the stick-slip effect can be resolved. On the other hand, a cause for the change in motion can be revealed by determining the forces acting on the body, since it becomes apparent here that the acting frictional force varies.
Figure 2. Schematic representation of the experimental setup for determining the distance $d_1$ covered by the body $K_1$ over the friction surface and for synchronously determining the measured tension force $F_{\text{string}}$.

The friction force $F_{\text{LF}} = \mu_{\text{LF}} \cdot F_N$ acts (see area 3 in figure 1). $\mu_{\text{LF}}$ is the equivalent of $\mu_{\text{sl}}$ for the case that body $K$ moves relative to the friction surface. Accordingly,

$$F_{\text{LF, max}} > F_{\text{LF}} \iff \mu_{\text{LF}} > \mu_{\text{sl}}$$

Applies to the ratio of maximum static frictional force $F_{\text{LF, max}}$ and kinetic frictional force $F_{\text{LF}}$ as well as their associated friction coefficients.

If the friction coefficients are strongly different, i.e.

$$\mu_{\text{sl}} \gg \mu_{\text{LF}},$$

the stick-slip effect occurs [17]. The stick-slip effect is explained by the fact that, due to the very different mechanical properties of the friction surface and body $K$, the sliding phase is directly slowed down again by recoil forces, since body $K$ interlocks with the friction surface again with a very high probability. Body $K$ at rest corresponds on the one hand with the stick phase (see area 5 in figure 1), and body $K$ in motion corresponds on the other hand with the slip phase (see area 4 in figure 1). The static frictional force $F_{\text{LF}}$ occurs in each case in the stick phase and the kinetic frictional force $F_{\text{LF}}$ in the slip phase.

2.2. Experimental setup

In order to make the stick-slip effect quantitatively measurable, we refer to an experiment of physicist Coulomb (1736–1806), who accelerated a body (in our setup body $K_1$ with mass $m_1 = 3.5$ kg) uniformly over a friction surface [18] via a second body (in our setup body $K_2$ with mass $m_2 = 1.4$ kg). For this purpose, in our setup (see figure 2), we connect both bodies via a string, with the string passing over a pulley so that body $K_2$ can be dropped. For this purpose, a thin and stable string is used, which does not significantly lengthen when body $K_2$ is attached. The string and the pulley are assumed to be massless.

To enhance the stick-slip effect, it is necessary to increase the ratio of the friction coefficients. For this reason, we use metal as...
the material of body $K_1$ and a corkboard for the friction surface because they have large differences in their surface properties. The friction generated by the string on the pulley is neglected in the following considerations, as this amount of friction force is very small compared to the friction force $F_f$ between body $K_1$ and the friction surface.

In addition, we integrate two digital sensor boxes into the experimental setup: a distance sensor [19] and a force sensor [20]. The distance sensor is mounted on body $K_1$ and measures the distance $d_1$ to a wall by means of a time-of-flight ultrasonic measurement with an uncertainty of $u_{\text{distance}} = \pm 0.5$ mm. The force sensor is connected to body $K_2$ via a string and measures the tension force $F_{\text{string}}$ using the strain gauge method with an uncertainty of $u_{\text{force}} = \pm 15$ mN. The corresponding experimental setup is shown schematically in figure 2 and implemented in figure 3.

By dropping body $K_2$, the weight $F_{G2}$ of body $K_2$ together with the weight $F_{G,\text{ForceSensor}}$ of the force sensor act as a dragging force $F_D = F_{G2} + F_{G,\text{ForceSensor}}$ on body $K_1$ and accelerates it. The weight of the force sensor $F_{G,\text{ForceSensor}}$...
is small compared to the weight of body $K_2$ and is therefore neglected in all further considerations.

To start the measurement, the sensor boxes must be connected to a device (in this case, an iPad) in which a corresponding measurement acquisition software is installed (the software measureAPP [21] in version 14.0.0, as provided by the sensor manufacturer). The sensors used are activated in measureAPP, the sample rate is set accordingly, and the data acquisition is started. Body $K_2$ is then dropped manually, and the tension force $F_{\text{string}}$ and the distance $d_1$ to the wall are recorded automatically by measureAPP.

For physics lessons, it is useful to display the measured values directly in graphical form. For our purposes, the measured data is exported from measureAPP and visually prepared via LaTeX.

At any time $t$ the friction force $F_F$, the weight $F_{G2}$, as well as the tension force $F_{\text{string}}$ accelerate the system with $a$ (as viewed from the inertial frame of reference). The system consists of the two bodies $K_1$ and $K_2$ connected to the string. Figure 2 shows the acting forces, their points of application and their direction. By simply adding up the acting forces for each of the bodies, we obtain the resulting forces on the bodies $K_1$ and $K_2$ as

$$F_{\text{string}} - F_F = m_1 \cdot a$$

(3)

for body $K_1$ and

$$F_{G2} - F_{\text{string}} = m_2 \cdot a$$

(4)

for body $K_2$. From equations (3) and (4) we obtain the tension force $F_{\text{string}}$ measured by the force sensor to be

$$F_{\text{string}} = m_1 \cdot a + F_F = F_{G2} - m_2 \cdot a.$$  

(5)

Applying Newton’s Second Law we obtain

$$F_{G2} - F_F = (m_1 + m_2) \cdot a.$$  

(6)

In the static case, when the entire system is not moving ($v = 0$), the frictional force $F_F$ equals the weight $F_{G2} = F_{G2}$. In the dynamic case, the weight $F_{G2}$ is greater than the frictional force $F_{\text{string}}$ and $m_1 \cdot a = F_{G2} - m_2 \cdot a$ applies to body $K_1$. Thus, if a static frictional force $F_{\text{static}}$ acts on body $K_1$, the measured force $F_{\text{string}}$ is greater than if a kinetic frictional force $F_{\text{kinetic}}$ acts.

In terms of the motion of body $K_1$, this means that if the measured tension force $F_{\text{string}}$ is relatively large or increasing, the frictional force $F_F$ is large or increasing, and body $K_1$ slows down or is in a resting state. If, on the other hand, the measured tension force $F_{\text{string}}$ is relatively small or decreasing, the friction force $F_F$ is small or decreasing, and body $K_1$ is accelerating or in a sliding state, the distance $d_1$ between body $K_1$ and the wall increases, and in the adhesive state, distance $d_1$ remains constant because body $K_1$ is not moving.

### 2.3. Analysing two measurement data sets with two different sample rates

As described in section 1, the purpose of this paper is to show that ‘big data’, generated by means of measurement by a high sample rate, lead to more and different observations than using analog measurement acquisition methods. For this goal, we perform the experiment described in section 2.2 with a low sample rate of ten samples per second (generating a small data set) and a higher sample rate of 50 samples per second (generating ‘big data’).

Figure 4 shows a section of one second of the measured tension force $F_{\text{string}}$ as well as the actual position $d_1$, after body $K_1$ has already started moving.

The small data set shows (a) an approximately relative uniform measured tension force $F_{\text{string}}$, as well as (b) an accelerated body $K_1$. (We want to stress here that this is not a uniformly accelerated motion, since the acceleration is not constant due to the resulting force not being constant. So, one cannot accept a $d \propto t^2$ graph.) It can be concluded here from the measurement data that body $K_1$ is characterised as being in a continuous sliding state.

The ‘big’ data set, generated by means of measurement by a high sample rate, in contrast to the small data set, does not show a constant measured tension force $F_{\text{string}}$. In contrast, the ‘big’ data set shows (a) an oscillating measured tension force $F_{\text{string}}$ and (b) a body $K_1$ in an alternating motion. A 0.2 s excerpt of ‘big data’ shown in figure 5 shows more clearly the relationship...
between the measured tension force $F_{\text{string}}$ and the motion of body $K_1$. The distance $d_1$ travelled increases when the measured tension force $F_{\text{string}}$ decreases. On the other hand, if the measured tension force $F_{\text{string}}$ increases, body $K_1$ remains stationary ($d_1$ is constant in this phase). It can be concluded here from the measurement data that body $K_1$ does not move permanently relative to the friction surface, but body $K_1$ is alternately at rest and in motion. This rapid change of motion states of body $K_1$ in combination with the relationship with different types of friction force $F_F$ are empirical evidence for the stick-slip effect.

The ‘big’ data set allows different or competing conclusions compared to the small data set: first, it can be resolved that body $K_1$ does not move constantly accelerated over the friction surface, but that body $K_1$ permanently alternates at rest and in motion. Thus, ‘big data’ holds empirical evidence for the stick-slip effect due to the changing motion states. Second, it can be resolved that two different types of frictional force $F_F$ (static frictional force $F_{\text{sf}}$ and kinetic frictional force $F_{\text{kf}}$) act on body $K_1$, since $F_{G2}$ is constant. Combining the two aspects, it can be concluded that ‘big data’ resolves that, depending on the state of motion, a different form of frictional force $F_F$ acts on body $K_1$, and therefore, the frictional force $F_F$ is the cause of the change in motion.

3. Conclusion

A comparison of the conclusions of the two differently sized measurement data sets and those in our example above shows that ‘big data’ can generate added value for experimentation in physics classes. This is based on the fact that an increasing sample rate makes it possible to better detect changes in the measured quantities. In this way, we were able to uncover the stick-slip effect in our example, which was previously impossible with analog measurement methods. Once again, we want to stress that both data sets are based on the same physical phenomenon and experimental inquiry. The only difference is a characteristic of the measurements taken: the sample rate!

In our example, we have generated ‘big data’ not only by increasing the sample rate, but also via the number of simultaneously measured quantities. The simultaneous acquisition of several measurement variables would not have been
necessary in this example because the stick-slip effect could have been detected by a higher resolution of the covered distance $d_1$ alone. Nevertheless, we decided to measure the two variables (tension force $F_{\text{tension}}$ and the distance $d_1$ travelled) simultaneously in order to be able to describe the cause of the change in motion of body $K_1$. There is also didactic potential behind the acquisition of several measured variables synchronously, which consists, among other things, of the fact that causes of changes in the state of motion can be directly uncovered.

In summary, we have been able to demonstrate that larger amounts of measurement data (generated by measuring with a higher sample rate and through the parallel acquisition of two measured quantities) can lead to the quantitative assessment of phenomena. However, not only can data sets generated by the use of digital data acquisition systems exploit this potential resulting from larger data sets, so can the use of online data repositories as a data source, as described in [22, 23]. These online repositories also exceed the threshold of ‘big data’ as proposed by [8] for physics education compared to data sets acquired by hand. Against the backdrop of ongoing discussions around digitalisation in science and especially physics classes, we hereby call on the community (practitioners and researchers) not only to use digital measurement in teaching, but also to consider the didactic potential it offers.

Data availability statement
The data that support the findings of this study are available upon reasonable request from the authors.

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