普通高等学校双语教学规划教材

Experimental College Physics

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西安电子科技大学出版社
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内 容 简 介

本书是专门为外国留学生、合作办学学生和准备出国留学的学生编写的物理实验教材，所选实验内容紧扣大学物理教材，介绍了常用物理量的测量、常用仪器的结构及使用，涵盖测量方法、误差理论、数据处理、力学、电学、光学等内容。全书共编入 21 个经典实验，其中力学 5 个、光学 7 个、电学 9 个。

本书可作为高等院校各专业的物理实验双语教材，也可作为教师或科技人员的参考书。

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前 言

“大学物理实验”是高等工科院校课程体系中一门重要的基础课程，也是大学生进校后的第一门科学实验课程。该课程旨在为后续专业实验和科学研究奠定基础，不仅要讲授学生开展实验工作所需具备的基本知识、基本方法和基本技能，更要培养学生观察问题、分析问题和解决问题的科学思维与创新意识，以及理论联系实际的能力。

随着国际交流日益频繁，高等教育国际化是不可扭转的趋势。为适应国际化教育发展的需要，在西安电子科技大学物理实验中心、教务处和出版社的大力支持下，作者以中文版《物理实验》(西安电子科技大学出版社，2007)为基础，结合多届外国留学生的教学经验，编写了本书。本书的编写已被纳入西安电子科技大学“十三五”规划教材建设。

大学物理实验是集体教学活动，本书凝结了物理实验中心全体教师的集体智慧和辛勤劳动。本书编写过程中得到了许多教师的大力支持，同时参考了国内外其他高等学校的同类教材，在此一并表示衷心感谢！还要感谢本书的审译——延安大学外国语学院的侯娟娟老师付出的辛勤劳动。

实验教学探索是永无止境的任务，加之编写时间仓促及编者业务水平有限，书中难免有不妥与疏漏之处，恳请同行及广大读者提出宝贵意见。

编　者

2016 年 5 月

Preface

Experimental College Physics has 21 experiments including mechanics, electricity and optics. It aims to provide "hand-on" experiences of various physical principles and to augment and supplement the learning and understanding of basic physical principles, while introducing laboratory procedures, techniques, and apparatus. In so doing, students become familiar with laboratory equipment, procedures and related scientific methods. In this book, the theory of physical principles is presented in experiments, and the predicted result will be tested by experimental measurements. Even those well-known principles, which may have been tested many times before, are included within some accepted theoretical or measured values. But to be best, you should imagine that you are the first person to perform an experiment to test a scientific theory.

Basically, the textbook is designed for students who are taking their first course in physics, and the order of the subject matter of the experiments is approximately that found in most standard textbooks for first-year college physics. Moreover, the apparatus in all the experiments is of simple design and could be found in most physics laboratories practically. Authors believe that the fundamental principles of physics can best be learned through the use of simple apparatus. If high precision is required in a first course, much of the understanding of fundamental principles is sacrificed to acquiring skill in operating complex equipment.

In addition to the list of apparatus, the instructions for each experiment include a statement of the purpose of the experiment, an introduction summarizing the physical principles involved, and directions for the experimental procedures. A description of the

operation and use of the apparatus is included in some of the experiments where such an explanation seems necessary. Questions which follow some experiments are designed to aid students in making more careful observations and to train them to analyze these observations and interpret the results. The authors believe that the answers to these questions give a very clear indication of the student's grasp of the experiment, and are a very important part of the report handed in to the instructor.

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Part Ⅰ

Introduction to Experimental Uncertainties and Error Analysis

1. No Information without Uncertainty Estimation

XIY is about 59 minutes from the south campus of Xidian University by car. You can learn this from the driving directions on Google Maps, and it is a useful piece of information if you are checking out possible travel bargains. But what if you already have reservations out of XIY and need to know when to leave campus for the airport? Then you'd better know that the drive can easily take as little as 45 minutes or as much as an hour and a half, depending on factors you cannot possibly determine in advance.

Similar comments apply to a vast array of numbers we measure, record, and trade back and forth with each other in our everyday life. I will be off the phone in five minutes—or maybe two to eight minutes. We set the oven to 350°, knowing that the actual temperature might be only 330° when the preheat light goes off.

Just about every number in our lives is actually a stand-in for a range of likely values. Another way of putting this is to say that every value comes with an *uncertainty*, or an *error bar*. I will be off the phone in 5 ± 3 minutes; the oven temperature is 350 ± 25 degrees, and so on. Sometimes a quantity does have zero error bars: I have exactly one brother. More often, though, numbers have error bars and we ignore them only through the ease of familiarity.

When a situation is unfamiliar, though, suddenly it can be very important to ask about the error bars. Without error bars on the travel time to XIY, you may very well miss your flight. Your dorm room may be about three meters wide, but lugging home that used couch will seem pretty dumb if the room is actually 3 meters $\pm$ 5 cm! And it is not just numerical values that can have uncertainties attached to them.

Uncertainties—how to think about them, estimate them, minimize them, and talk about them—are a central focus of Physics experiment. We will learn a handful of statistical definitions and methods, but we will concentrate on whether they make sense rather than whether we can justify them rigorously. Our goal is that we ourselves should be able to talk and think reasonably about the experimental situations we encounter in the lab each time.

2. What is an Error Bar?

In a laboratory setting, or in any original, quantitative research, we make our research results meaningful to others by carefully keeping track of all the uncertainties that might have an appreciable effect on the final result which is the object of our work. Of course, when we are doing something for the very first time, we do not *know* beforehand what the result is going to be or what factors are going to affect it most strongly. Keeping track of uncertainties is something that has to be done before, during, and after the actual 'data-taking' phase of a good experiment. In fact, the best experimental science is often accomplished in a surprisingly circular process of designing an experiment, performing it, taking a peek at the data analysis, seeing where the uncertainties are creeping in, redesigning the experiment, trying again, and so forth. But a good rule is to estimate and record the uncertainty, or error bar, for every measurement you write down.

What is an error bar and how can you estimate one? An error bar tells you how closely your measured result should be matched by someone else who sets out to measure the same quantity you did. If you record the length of a rod as 95.0 ± 0.05 cm, you are stating that another careful measurement of that rod is likely to give a length between 94.95 cm and 95.05 cm. The word "likely" is pretty vague, though. A reasonable standard might be to require an error bar large enough to cover a majority—over 50%—of other measurement results.

However, it is convenient to have some sort of standard definition of an error bar so that we can all look at each other's lab notebooks and quickly understand what is written there. One common convention is to use "one sigma" error bars; these are error bars which tell us that 68% of repeated attempts will fall within the stated range. The 68% figure is not chosen to be weird, but because it is easy to calculate and convenient to work with in the very common situation of something called 'Gaussian statistics.' We will not go into this in detail, but here is one example of how useful this error bar convention can be: for many, many situations, if 68% of repeated attempts are within one error bar of the initial result, 95% will be within two error bars. The essential point here is that your error bars should be large enough to cover a majority, but not necessarily a vast majority, of possible outcomes.

Finally, an error bar estimates how confident you are in your own measurement or result. It represents how well you did in your experimental design and execution, not how

well the group at the next bench did, or how well your lab manual was written. Error bars are part of your data and must follow logically from what *you* did and the observations *you* made; anything else is fraudulent data-taking.

3. Random Errors, Systematic Errors, and Mistakes

There are three basic categories of experimental issues that students often think of under the heading of experimental error, or uncertainty. These are random errors, systematic errors, and mistakes. In fact, as we will discuss in a minute, mistakes do *not* count as experimental error, so there are in fact only two basic error categories: random and systematic. We can understand them by reconsidering our definition of an error bar from the previous section.

An error bar tells you how closely your measured result should be matched by someone else who sets out to measure the same quantity you did. How is this mysterious second experimenter going to measure the same quantity you did? One way would be to carefully read your notes, obtain your equipment, and repeat your very own procedure as closely as possible. On the other hand, the second experimenter could be independent minded and could devise an entirely new but sensible procedure for measuring the quantity you measured. Either way, the two results are not likely to be exactly the same!

3.1 Random Errors

Random errors usually result from human and from accidental errors. Accidental errors are brought about by changing experimental conditions that are beyond the control of the experimenter, such as vibrations in the equipment, changes in the humidity, and fluctuating temperatures. Human errors involve such things as miscalculations in analyzing data, the incorrect reading of an instrument, or a personal bias in assuming that particular readings are more reliable than others. By their very nature, random errors cannot be quantified exactly since the magnitude of the random errors and their effect on the experimental values is different for every repetition of the experiment. So statistical methods are usually used to obtain an estimate of the random errors in the experiment.

3.2 Systematic Errors

A systematic error is an error that will occur consistently in only one direction each time the experiment is performed, i. e., the value of the measurement will always be greater (or lesser) than the real value. Systematic errors most commonly arise from defects

in the instrumentation or from using improper measuring techniques. For example, measuring a distance using the worn end of a meter stick, using an instrument that is not calibrated, or incorrectly neglecting the effects of viscosity, air resistance and friction, are all factors that can result in a systematic shift of the experimental outcome. Although the nature and the magnitude of systematic errors are difficult to predict in practice, attempt should be made to quantify their effect whenever possible. In any experiment, care should be taken to eliminate as many of the systematic and random errors as possible. Proper calibration and adjustment of the equipment will help reduce the systematic errors leaving only the accidental and human errors to cause any spread in the data. Although there are statistical methods that will permit the reduction of random errors, there is little use in reducing the random errors below the limit of the precision of the measuring instrument.

4. How to Estimate Error Bars in Data

Since we are not going into Gaussian (let alone other) statistics, our definition of an error bar remains loose enough so that we should not be too concerned over the exact numerical value we assign to error bars in our experiments. However, we do want to base our error bars on experimental reality, so they can be useful in clarifying our data analysis and results in the end. The overall uncertainty of a result tells us how much trust to place in the specifics of the result. Beyond that, however, identifying the major source(s) of the final uncertainty can guide us in spending our time and effort productively, should we wish to redesign the experiment for better results in the future.

So, how do we assign an error bar to a measurement taken in the lab? Several specific but common situations are covered below. The zeroth rule of error estimation, though, is that we should always think about the meaning of an error bar and assign an error bar that makes sense based on that meaning.

One of the simplest sources of uncertainty is the resolution or quoted accuracy of a measuring device. Many lab devices, such as electrical meters and mass balances, have resolutions specified by their manufacturers. These device uncertainties can be read off the device (sometimes on the bottom surface) or in its manual. However, something as simple as a meter stick also has an effective device resolution. If the stick is marked every millimeter, for example, then if an object ends between the 101 and 102 mm marks it is probably unreasonable to expect observers to do any better than choosing which mark is closer. In this way, an object that is truly 101.4 mm long would be measured at 101 mm,

while a 101.8 mm object would be recorded as 102 mm long. A reasonable error bar for the device resolution of the meter stick, then, would be ± 0.5 mm. A device resolution uncertainty can be estimated for just about any measurement device by considering its construction and the reliability of a reasonable observer.

Another source of uncertainty, sample variation, becomes important when we measure a phenomenon that just does not quite come out the same every time. In a hypothetical bean sprout study, we conduct the experiment on more than one plant because we suspect there is random variation from one bean sprout to another. Measuring several plants and taking the mean of their heights seems like a natural way to find out something about average bean sprout growth. Just as importantly, though, measuring several plants gives us an idea of how strong the random variation might be and thus how far off the average might still be from the "true" mean. If we measure twenty plants and all twenty are the same height to within a millimeter, we can be fairly certain that we know the average bean sprout height to better than a millimeter (barring systematic errors). On the other hand, if we measure two plants and their heights are 21.00 cm and 22.00 cm, we should be pretty wary of reporting the overall average to be 21.50 cm. In the next section we will develop formulas for quantities called the *standard deviation* and *standard error* that can be used to find random uncertainty in a quantity based on repeated sampling like this.

The error estimation techniques we have just discussed apply primarily to random errors. How can we estimate systematic errors? First we must consider possible causes of systematic error, then estimate reasonably from theoretical knowledge, additional experiments, or prior experience how much effect these causes might have. If we are measuring the length of a metal rod, the length might reasonably depend on temperature. Perhaps the temperature in the room could be as much as three degrees different from standard 'room temperature' definitions. How much shift could that cause in the rod's length? If we have no experience or reference materials to guide us, we could deliberately cool the rod in a refrigerator, measure the new length, and estimate roughly how much length change occurs per degree. This technique of deliberately exaggerating an effect to estimate its significance is often useful in dealing with systematic errors.

There is one more cardinal rule of error sources: "human error" is *never* a legitimate source of error. That phrase is completely uninformative, and should never be used as an insurance or catch-all in discussing an experiment. Humans cause error, of course, but in specific ways that can be described and quantified.

5. Sample Mean, Standard Deviation, and Standard Error

In this section we develop formulas to quantify a measurement and its random error, based on taking the measurement repeatedly in what is supposed to be the same way (this is sometimes called sampling). This is probably the most mathematical section of our error analysis discussion, but even here we will give reasons why our formulas are reasonable without actually rigorously deriving them.

Imagine we sample a quantity repeatedly, yielding measurements $(x_1, x_2, \cdots, x_N)$. While we try to make all the measurements identical, random variation shows up in our list, so to estimate an overall result we quite naturally take the mean:

$$\bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} \tag{1.1}$$

Perhaps we have done $N=10$ repetitions. If we kept going to $N=20$ how would the value of x change? What if we kept going even longer? In other words, how much uncertainty is left in our measurement because of our limited sampling of the random variation? To answer this question, it is useful to step back a bit first.

When we want to combine all N measurements into a single representative result x_{rep}, it is easy and natural to take the mean: $x_{\text{rep}}=\bar{x}$. But why is $\bar{x}$, as defined in Equation (1.1), really the best candidate for x_{rep}? It would be nice to come up with some measure of deviation which is minimized, sample-wide, by this choice. Perhaps we should be trying to minimize the distance between the individual data points and x_{rep}.

That is, maybe we should minimize $\sum_{i=1}^{N} |x_i - x_{\text{rep}}|$. This is a nice thought, but it turns out that $x_{\text{rep}}=\bar{x}$ does *not* minimize this particular deviation measure…so this must not be the right deviation measure to think about if we are taking sample means. On the other hand, it turns out that $\sum_{i=1}^{N} (x_i - x_{\text{rep}})^2$ is minimized by taking $x_{\text{rep}}=\bar{x}$. To see this, we can differentiate the expression with respect to x_{rep} and set the derivative equal to zero:

$$\frac{\mathrm{d}}{\mathrm{d}x_{\text{rep}}}\left(\sum_{i=1}^{N} (x_i - x_{\text{rep}})^2\right) = 0 \qquad x_{\text{rep}} = \frac{\sum_{i=1}^{N} x_i}{N} = \bar{x} \tag{1.2}$$

Indeed, the sample mean is the representative value that minimizes the *sum of the*

squares of the individual deviations. So if the sample mean is a good measure of the overall result, something related to this summed-squared deviation should be a good measure of the overall result's uncertainty!

Let us begin by imagining that we take an $(N+1)^{th}$ measurement. How far from the previous mean is this single, new measurement likely to be? Well, we can use the summed-squared deviation to help us guess, but probably we should divide the sum by N first to turn it into a mean-squared deviation: $\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2$. This still is not a good measure of deviation, since it is still squared—if the measurement is a length in centimeters, for example, this thing is in cm^2 so it can not be a deviation. Therefore we will take the square root: $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2}$ is called the *root mean square* deviation, or *r. m. s.* deviation for short, and it is a useful measure of how far from the mean a single measurement is likely to fall. It turns out that, by doing proper Gaussian statistics, one comes up with a slightly more generous (i. e., larger) estimate of individual deviation from the mean. Thus we define a quantity called the *standard deviation*:

$$std.\ \text{deviation} = \sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2} \tag{1.3}$$

The standard deviation is used to estimate how far from the mean a single measurement is likely to fall.

Originally, though, we were trying to answer a different question. We wanted to know how far our calculated mean was likely to be from the true, or ideally and infinitely well sampled, mean. *This* is the uncertainty of our final (mean) result, and we call it the ***standard error*** or ***standard deviation of the mean***. If we increase the number of samples N, the standard deviation defined in Equation (1.3) will not in general get smaller. But certainly taking more measurements in our sample ought improve the standard error. Each new measurement we add won't necessarily make x closer to the ideal, but in general we will creep and wander towards the ideal value. Therefore, the standard error is given by:

$$std.\ \text{Err} = \frac{\sigma}{\sqrt{N}} = \frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2}}{\sqrt{N}} \tag{1.4}$$

To sum up this rather lengthy discussion of repeated trials or samples: