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LearnPIV: An Interactive, Web-Based Learning Tool for Particle Image Velocimetry Basics

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Introduction

This paper introduces LearnPIV.org, a freely available, interactive, web-based simulation tool designed to aid students, instructors, and novice engineering professionals in learning the basics of Particle Image Velocimetry (PIV) methods. PIV is a state-of-the-art optical flow visualization and measurement experimental technique that is well-established in modern research and engineering practice. The basic methods for PIV include using synchronized laser sheet optics and digital cameras to record the locations of neutrally buoyant, light scattering particles that follow a flow of interest. These locations are converted into velocities by computer algorithms, and engineers use these velocity vector fields to identify flow characteristics and parameters of interest. This *flow field* visualization and measurement technique is uniquely suited to allow engineers and engineering students to interact, observe, and measure real world flows. Specifically, PIV is minimally invasive, requiring only optical access to the seeded flow. PIV also provides a whole field measurement, allowing users to gather flow velocity measurements at all (two-dimensional for the methods described) points in a flow field simultaneously. Further, PIV visualizes the flow, allowing experimentalists to qualitatively consider the flow concurrent with their quantitative results.

However, attaining quality PIV results typically depends on experienced users and/or well bounded experiments. To allow more users to interact with PIV in educational settings and to reduce time to competency for early professional PIV users, we sought to develop an interactive, no-cost learning tool for teaching PIV basics. To accomplish this goal, we first identified key aspects of PIV data and processing most relevant to PIV output quality, to include image density, particle image diameters, and interrogation region size [1, 2]. With these parameters identified, we developed a synthetic image generator in the Python coding language for the purpose of allowing learners to explore the impacts of each parameter by defining, generating, and analyzing synthetic PIV images. To increase the accessibility of this tool, we incorporated the synthetic image generator into a Django web framework [3] and hosted the site through the Heroku web-hosting platform [4] to create the final tool, accessible at LearnPIV.org.

LearnPIV.org incorporates the synthetic image generator with a series of learning content modules that describe PIV analysis, digital camera operation, and the effects of experimental PIV parameters. Together, these modules provide users with an easily accessible and interactive resource to support implementation of basic PIV experiments as well as more advanced PIV techniques. With this tool, educational and early professional PIV users are equipped to understand the how PIV algorithms work and, resultantly, can improve their own data collection and analysis.

PIV Background

Since its initial development in the late 20th century [5, 6], PIV has become the state-of-the-art flow visualization and measurement technique. Standard PIV experiments consist of a flow field, seed particles, laser, laser optics, and digital camera. Specifically, seed particles are discrete, neutrally buoyant (to avoid gravitational effects) spheres (near 1-100 μm in diameter) that are small enough to follow the flow field and large enough to scatter sufficient light for imaging by a digital camera. Seed particles are illuminated by a light sheet generated by a laser source and optics (i.e., cylindrical lens). The laser provides cohesive, directional, monochromatic light and the cylindrical lens spreads this light into a thin sheet. The combination of seed particles and light sheet illuminate a 2D plane of the seeded flow field so that the experimenter may observe fluid motions and structures as shown in Figure 1.

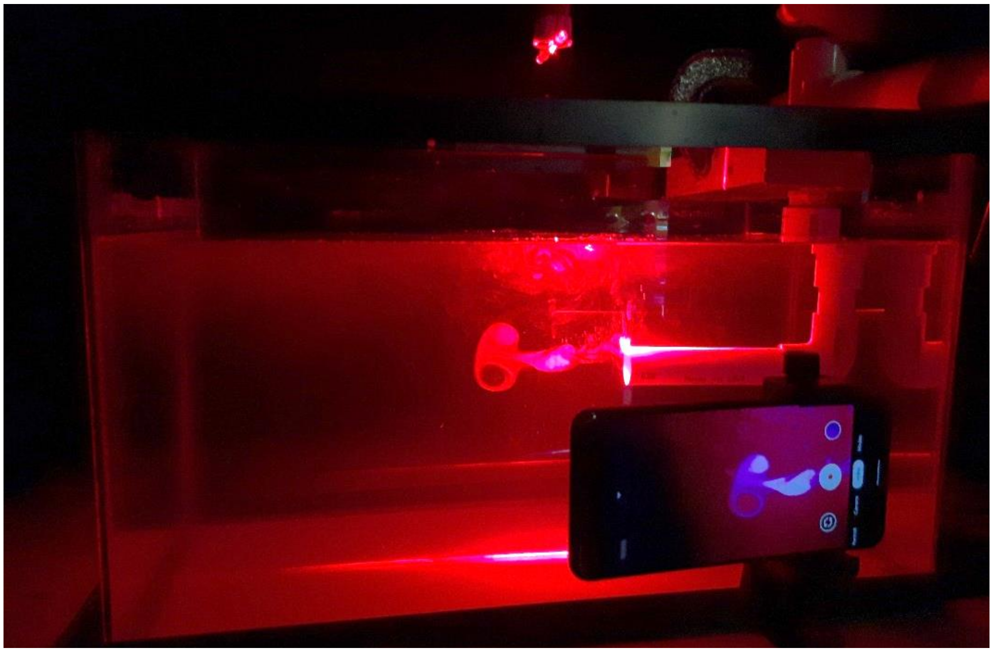


Figure 1. Demonstration of planar flow field visualized by laser light sheet and seed particles, then recorded by a digital camera. Note, only the pipe was seeded with particles to allow a single image frame to distinguish the vortex ring flow field of interest.

Beyond flow visualization, observers become quantitative experimenters by using digital cameras to image, and thus record, the locations of discrete seed particles in the flow in time. The instantaneous motion of the flow within discrete areas, or *interrogation regions,* of the image pairs are calculated by applying cross-correlation algorithms of digital image pair data recorded a known time apart. This calculation of the instantaneous motion of fluid flow within interrogations regions is referred to as Particle Image Velocimetry or PIV. Figure 2 provides the PIV result of imaging the vortex ring flow depicted in Figure 1. As shown in Figure 2, images A1 and A2 are cross-correlated, using 64x64 pixel interrogation regions, to calculate the velocity vector field (B).

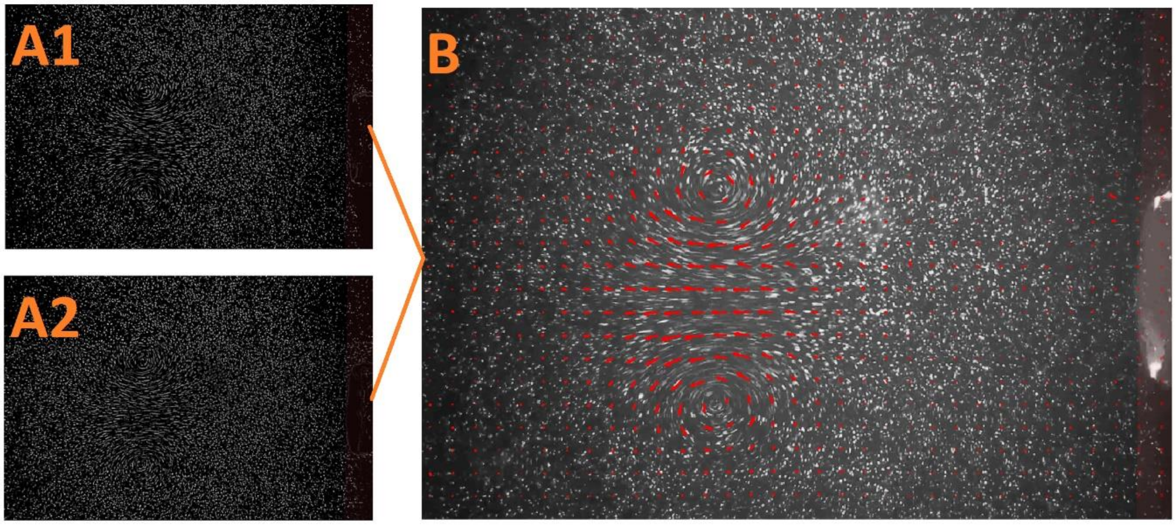


Figure 2. Demonstration of PIV images and results. A) Demonstrates consecutive (A1, dt=1/60s, A2) raw smartphone images of a vortex ring in water seeded with 100μm hollow glass spheres and illuminated by a~5mW laser and glass stir stick lens. B) Demonstrates the resulting vector field from PIV analysis correlating 64x64 pixel interrogation regions.

Professional PIV

In the science and engineering domains, PIV is often used to qualitatively identify and quantitively measure the motion of discrete small regions within a larger image. Examples include research on flow over aircraft [7], animals [8], and cars [9]. More recent application of PIV within novel fluid dynamics contexts includes hemodynamics in the Carotid Artery [10], fuel cell design [11], and breath flows relating to COVID-19 transmission [12]. Further, PIV based techniques are now used within non-traditional fluid dynamics contexts, to include estimating insect traffic [13], identifying soil-pile interactions [14], and tracking the movement of geophysical flows such as avalanches [15].

Researchers have also extended use of PIV methods beyond two-dimensional planar flows. An example of this extension is three-dimensional stereoscopic PIV, which provides a third velocity component inside the light sheet by using two cameras at separate angles [16]. Additionally, tomographic PIV commonly uses three or more cameras and a laser volume rather than a sheet to provide a larger region with the third velocity component than stereoscopic PIV [17]. Further, two- or three-dimensional Particle Tracking Velocimetry (PTV) allows researchers to conduct analysis similar to interrogation region-based PIV (tracking regions of particles) with higher resolution (tracking individual particles) [18]. These advances have even opened the field to estimating pressure field measurements through PIV/PTV data [19]. In addition to the state-of-the-art in PIV, the flow visualization and measurement in PIV shows promise for actively engaging secondary, undergraduate, and graduate students with fluid dynamics concepts.

Educational PIV

Engineering students often encounter fluid mechanics for the first time midway through their undergraduate career, in a mathematics-heavy curriculum, with a perceived lack of relevance to the real world [20, 21]. Some educators have even observed these difficulties to dissuade students from pursuing fluids-specific careers [21]. However, educators have also noted that students' perceptions about fluid mechanics could be shifted in response to flow visualization instruction [21, 22]. As a result, fluid mechanics educators capable of implementing PIV in the classroom/laboratory are not only provided these benefits of flow visualization, but a concurrent flow velocity measurement. This combination allows educators to pair the excitement of flow visualization and interaction with real-world flow experimentation and measurement.

Adrian's 2005 review of PIV developments, near two decades old at the time of this writing, includes a final call to design and implement lower cost and potentially limited-use PIV systems: "Means should be sought to reduce total system costs by reducing the costs of light sources and cameras [6]." Recent developments in technology, including digital imaging, computers, and laser technology, have helped to realize this vision. Today, in addition to large and expensive PIV systems sold for professional, research, and demonstration use, several solutions to implement PIV in educational settings exist. Examples include the commercially available "all-in-one" systems which gather and process data such as FlowMaster Educational^{TM}, HEMOFLOW^{TM}, and miniPIV^{TM}. For users willing and able to gather data separately, MATLAB provides a free (with MATLAB license) PIV application for computing velocity fields and fluid flow parameters from PIV data [23]. Beyond MATLAB, open-source PIV algorithms in several coding languages are available in the freely available software library OpenPIV [24]. With these resources, engineering educators have successfully implemented PIV in classroom demonstrations and interactive laboratories as a part of teaching fluid dynamics [25-28].

Recent growth in educational PIV and the resulting issues related to equipment cost and required software fluency has led other researchers to develop user-friendly mobile PIV systems. Current mobile PIV applications, mI-PIV [29] and smartPIV [30], provide low cost, safe, and distributed PIV through use of smartphone cameras and the processing power of today's mobile devices to apply PIV algorithms. The advent of new mobile technologies able to provide undergraduate learners with interactive, state-of-the-art, real-world flow visualization and measurement experiences can enable engineering educators to reduce many of the issues found in traditional fluid mechanics education.

Difficulties in Implementing PIV among Educational and Professional Novices

While the advantages of PIV in science and engineering contexts are proven, there are several challenges associated with implementing PIV that complicate novice (educational or professional) use of PIV. One key issue is PIV's limited velocity dynamic range (i.e., the resolution of and difference in maximum and minimum resolvable velocities). Particle displacement magnitudes are traditionally maximized at one-quarter of the interrogation region size (in pixels/framerate) with a resolution near 0.1 pixels/framerate. Use of larger interrogation regions to increase maximum velocity range results in a loss of spatial resolution; this trade-off is the first of several that must be weighed when implementing PIV. A second issue results from the use of small, neutrally buoyant seed particles (that more closely follow the flow but scatter less light than larger diameter particles) and high camera shutter speeds that capture pairs of images that are very close together in time. To compensate for short exposures and small quantities of scattered light, increased laser power is required to adequately illuminate the particles for imaging. Use of high-power, pulsed lasers substantially increases the cost and safety risks of PIV systems. A third issue, which is of particular interest to this work, is the level of experience and "know-how" required of PIV experimenters, which includes awareness of the trade-offs in PIV imaging and processing, to gather viable data and produce accurate PIV results.

In addition, knowledgeable or expert PIV users are more likely to get useful results from their PIV analysis based on their understanding of PIV algorithms and digital imaging parameters. Usually, this understanding is gained through several years of education and practice using PIV. For example, image background noise (i.e., leaving objects which appear in the image background, allowing reflected light into the images, etc.) frequently leads to poor PIV images, and potentially inaccurate or even physically meaningless vector fields. An experienced PIV user understands this as the fact that substantial image background noise reduces the likelihood of the PIV algorithms finding a valid correlation peak. Lacking this knowledge, novice PIV users may achieve poor PIV results due to the allowance of background noise and be dissuaded from further engagement in the process. Similarly, images that are too dark can reduce the strength of the correlation peak and the quality of PIV results. Experienced users understand this issue, and how digital aperture, ISO, and shutter speed can be used to take properly illuminate images. Novice users, however, are less likely to understand how and why to apply these tools; their lack of knowledge about digital imaging often results in poor PIV results and experiences.

Beyond imaging, user selection of PIV processing parameters such as interrogation region size, primary peak ratio and background subtraction method are key contributors to the accuracy of PIV results [2]. In fact, poor selection of PIV processing parameters can lead to highly erroneous vector fields despite having ideal images. Further, PIV processing algorithms are becoming increasingly complicated as new and more powerful PIV algorithms are developed. A fundamental understanding of the underlying cross correlation techniques is critical to serve as a base on which more complicated algorithm understanding may build upon. Modern strategies to provide this basic understanding to novice PIV users include direct guidance (e.g., graduate students working in a laboratory with a research mentor or attending lecture series on PIV) and indirect guidance (e.g., reading journal publications on error sources and best practices for modern PIV [2, 31]). However, all current guidance strategies are limited in some way with respect to audience and accessibility. *As a result of these observations, we undertook this project to provide a tool for teaching early professional and STEM students about PIV imaging and processing basics in a broadly accessible manner.*

LearnPIV.org Development

The development of LearnPIV.org was conducted concurrently with our research on how to do PIV in educational settings. Specifically, we found that inexperienced PIV users often lack the prerequisite knowledge to reliably gather and analyze PIV data. To mitigate this issue, we chose to design an accessible web-based tool to support undergraduate and early professional PIV users who actively engage with PIV data and processing. Our methods in developing this tool followed a traditional design-based research process [32], beginning by identifying our final project goals, identifying several means to achieve those goals, developing an initial design, refining the initial design, and finalizing our solution.

Outlining Requirements

To start our requirements, we recognized that platform compatibility issues (e.g., Windows or Apple for PC users) often restrict the user base. Therefore, we chose a web-based platform to ensure our final solution could reach a broader number of users. Further, use of a web-based platform aligns with our goal to provide educational tools free to all users. Within LearnPIV.org, we desired to use the benefits of interactive learning. Therefore, we designed LearnPIV.org to provide an experimental module that enables users to select, vary, and see the outcomes of common image and processing parameters known to affect PIV output quality. Those parameters are:

- Particle Density
- Particle Image Diameter
- Out of Plane Motion
- Image Noise
- Interrogation Region Size
- Camera Bit Depth
- Particle Displacement

We included these parameters based on prior understanding of the variables most important to PIV error [1] and our observations of novice PIV users. To accomplish our goal of providing users with an interactive means for understanding the effects of these parameters without the need for gathering their own PIV data, we developed a synthetic image generator: a script for building artificial images similar to real-world PIV images according to a prescribed set of variables. To build the synthetic images, we recognized that *Particle Density* (the number of particles per image area), *Particle Image Diameter* (the size of particle images), *Interrogation Region Size* (the processing correlation matrix size), and *Camera Bit Depth* (the number of light intensity values a pixel may take) left little room for interpretation. However, to allow users to explore the varied nature of the remaining variables (i.e., Out of Plane Motion, Image Noise, Particle Displacement) we were required to make several assumptions and approximations.

Synthetic Image Generation

Users generating a synthetic image in our python-based synthetic image generator begins with uniformly randomly generated particle center locations *(x, y, and z)* within a padded interrogation region size array until the number of particles in the laser light sheet meets the desired particle density. We assumed diffraction limited particles which follow a gaussian light distribution with a maximum particle intensity value I_{pp} (the camera bit depth). With this assumption, we estimated the intensity value contribution I of particle i at a pixel located in the array (x,y,z) through Eq. 1 from Raffel et al. [33].

$$I_{x,y,i} = \int_{y_1}^{y_2} \int_{x_1}^{x_2} I_{pp}(z_i)\, e^{\frac{-8\left(\left(x-x_{o,i}\right)^2+\left(y-y_{o,i}\right)^2\right)}{l^2}} \tag{1}$$

After discretely evaluating Eq. 1 for the random particle locations, the synthetic image generator defines a particle displacement field according to the shear and displacement inputs. Specifically, the user defines the uniform displacement of the particles through the *X displacement* and *Y Displacement* variables (pixels/framerate). Then, the synthetic image generator adjusts these uniform displacements through the user-defined *Shear X* and *Shear Y* variables (pixels/framerate). To model the potential for particles to be lost/gained from the first and second image in an image pair (i.e., out of plane motion) we assumed the two-dimensional flow field is perfectly aligned with the calibration plane, and the laser sheet is misaligned from the *x*-direction of the calibration plane by a user-defined variable angle *Theta*. This misalignment of the laser sheet to the flow field results in a z-component of displacement equal to the cosine of the theta variable multiplied by the displacement along the angled direction. Equation 2 describes a particle's *z* location in frame *n+1* as a function of *x* displacement.

$$z_{n+1} = z_n + (x_{n+1} - x_n)\cos(\theta) \tag{2}$$

Empirical observations also show the noise in a digital camera is approximately lognormally distributed [1]. To reflect this, the synthetic image generator adds an intensity value to each particle according to a lognormal random distribution determined by the user-prescribed variables *Noise Mean* (the mean of the lognormal distribution) and *Noise SD* (the standard deviation of the lognormal distribution).

Finally, in addition to the standard synthetic image parameters (i.e., flow field, particle density, particle diameter, particle peak intensity, and region size), the synthetic image generator also allows the user to "streak" their images by prescribing the *Blur Count* (the number of particle images per single frame image), *ShutterU/ShutterV* (the space between single frame particle images), and *Frame Rate Ratio* (the space between particle images between image one and image two, determined through the Frame Rate Ratio*ShutterU/ShutterV to align with the flow physics). These variables are motivated by issues common to educational PIV, and for non-streaked particles (a streaked particles Boolean), the Blur Count is assigned a value of one. While the space between particle images and true particles from frame to frame is a function of the flow velocity, laser pulse frequency, and imaging equipment, these synthetic image inputs provide the streaking parameters in measurable terms which are easier to understand and visualize by the end-user. With these methods developed in Python, we developed a web-based GUI to allow a broad range of users to engage with the synthetic image generator.

Web Implementation

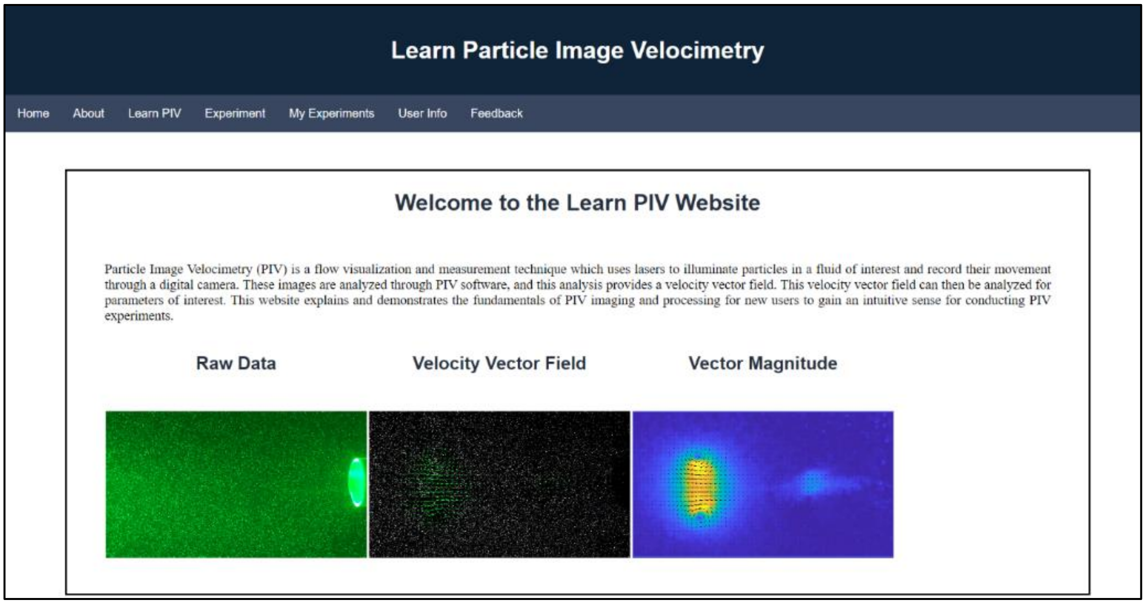
We created LearnPIV.org from a high-level Python web framework called Django. Our reasons for selecting Django were motivated by the completed, Python-based, synthetic image generator. With Anaconda (a distribution for scientific computing) and Spyder (an IDE bundled from Anaconda) we developed and tested the synthetic image generator for implementing with Django. The Django framework allowed us to not only run experiments of the same variables in a basic utils.py file, but the framework also allows a user to enter in values of their own.

Django provides a Form class which is used to create HTML forms. By creating Django Form objects, we prompt users for variable inputs. Certain combinations of variables caused the synthetic image generator to malfunction and/or take far too long to compute. For example, a high Particle Density increases the synthetic image generator runtime drastically. To resolve this issue, we constructed clean() functions in our Form objects to set a boundary condition for all our variables to within general limits of PIV data collection and analysis (e.g., region sizes must be between 8 and 128 pixels). The Django form and field validation evaluates users' inputs and inserts these inputs into the synthetic image generator to produce a list of graphs and values.

The synthetic image generator creates a Python class object from a utils.py file that contains a list of resulting graphs (the correlation plane and images) and PIV analysis values (r, s, signal to noise ratio, and error values). A Django Model (a single, definitive source of a SQL that contains the essential fields and behaviors of data) stores the list of resulting graphs and values. Additionally, our database stores user's inputs and presents them to the webpage after each experiment image generation is complete. The remainder of LearnPIV.org includes basic html files used for displaying PIV information and content. Isolating dependencies such as matplotlib, numpy, opencv, etc. in a virtual environment led us to cleanly deploy our Django application to a cloud-based platform called Heroku. Heroku takes the source code, and the list of dependencies to build the application and produces an executable website: learnpiv.com or learnpiv.org.

The LearnPIV.org Tool

The results of the synthetic image generator, web-based interface, and instructional .html content provide novice PIV users three modules for learning: 1) the Learning PIV module 2) the Experiment with a Single Variable module, and 3) the Experiment with Multiple Variables module. The Learning PIV module provides PIV learning content which contains text and figures describing fundamental concepts in simple terms. The Experiment with a Single Variable module provides users an interface to the synthetic image generator with the ability to vary a single image/processing parameter while all other variables are fixed. The Experiment with Multiple Variables module provides users an interface to the synthetic image generator and allows the user to prescribe every image/processing variable. The overall site is organized to contextualize the purpose of PIV (Figure 3 demonstrates the home page) and provide navigation to each module.



Welcome to the Learn PIV Website

Particle Image Velocimetry (PIV) is a flow visualization and measurement technique which uses lasers to illuminate particles in a fluid of interest and record their movement through a digital camera. These images are analyzed through PIV software, and this analysis provides a velocity vector field. This velocity vector field can then be analyzed for parameters of interest. This website explains and demonstrates the fundamentals of PIV imaging and processing for new users to gain an intuitive sense for conducting PIV experiments.

Figure 3. The LearnPIV.org home page.

Within the navigation on the home page (Figure 3), the About page provides a brief overview of the website and developers. The Learn PIV tab provides access to the Learning PIV module. The Experiment tab guides users to the Experiment with a Single Variable and the Experiment with Multiple Variables modules. The User Info provides users a means for each user to save and return to prior experiments. Finally, the Feedback tab provides a means for users to provide perceptions of and improvements for the current LearnPIV.org.

PIV Learning Module

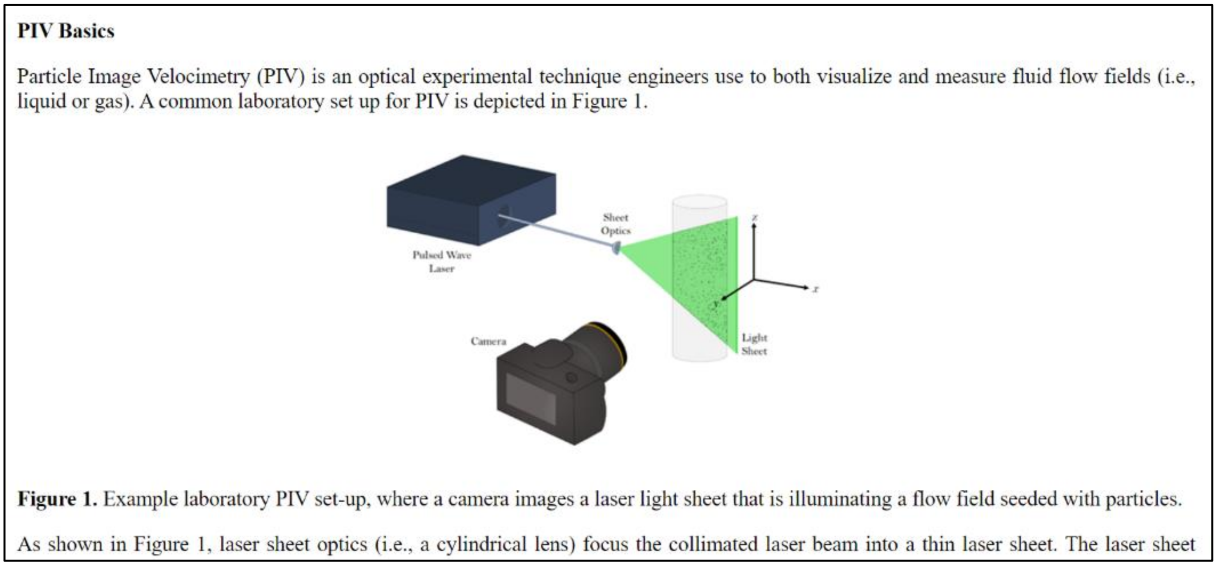
The purpose of the Learn PIV module is to provide textual and graphic information to explain the basics of PIV processing, imaging, and the synthetic image experiments. We identified three key areas of understanding necessary for LearnPIV.org. The first key area is the fundamentals of PIV algorithms, beginning with dividing images to interrogation regions, then cross correlating these regions, and ending by estimating the resulting vector value. The second key area of learning is basic digital camera operation, to include a description of pixels, ISO, aperture, etc. The final key area of learning is the basics of the synthetic image generator, which includes a description of the function of each variable and the influence each variable has on the resulting images. Table 1 summarizes the specific content for each section.

Table 1. The PIV learning content module categories and sub-topics.

Category	**Sub-topic**
How PIV Works	PIV Basics Cross Correlations Fast Fourier Transform Based Cross Correlations Sub-Pixel Estimation Multi-Pass Algorithms
Learn About Imaging	How Does a Digital Camera Work? Bit Depth Pixel ISO Shutter Speed Resolution Focus Frame Rate Aperture
Synthetic Images	Synthetic Image Summary Particle Image Diameter Theta Noise Mean and SD Region Size Camera Bit Depth X and Y Displacements Particle Density X and Y Shear

Each sub-topic contains a brief description and graphic representation with special emphasis placed on the topic's relationship with and importance to PIV measurements.

How PIV Works. The How PIV Works content aims to demonstrate the process of taking images of a seeded flow field and analyzing those images to identify a velocity vector field. To demonstrate the starting point of this content, Figure 4 depicts the beginning of the How PIV Works page.



PIV Basics

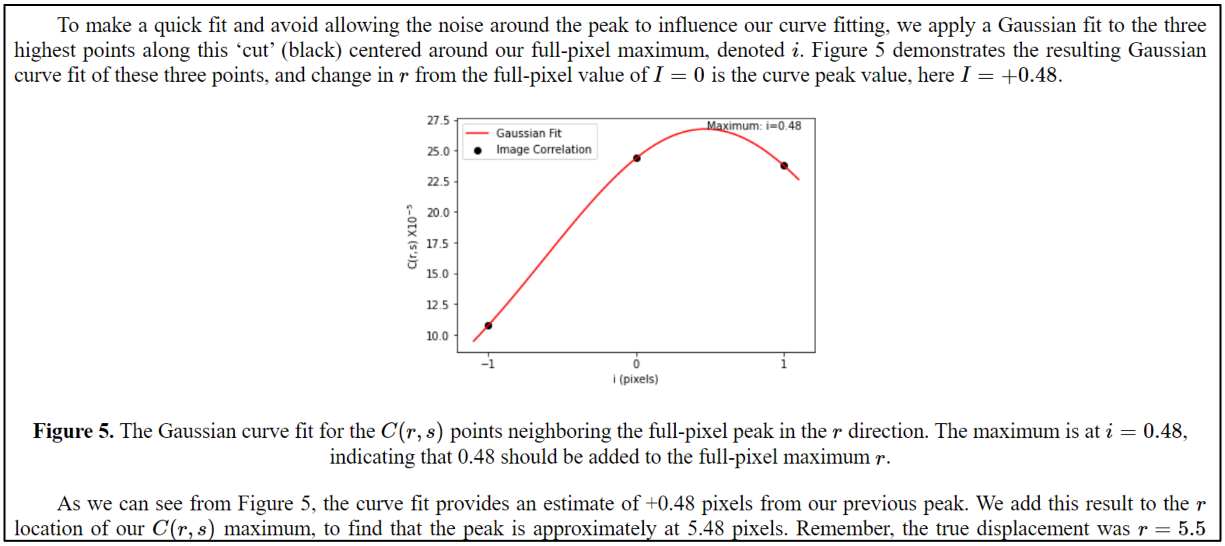
Particle Image Velocimetry (PIV) is an optical experimental technique engineers use to both visualize and measure fluid flow fields (i.e., liquid or gas). A common laboratory set up for PIV is depicted in Figure 1.

Figure 1. Example laboratory PIV set-up, where a camera images a laser light sheet that is illuminating a flow field seeded with particles.

As shown in Figure 1, laser sheet optics (i.e., a cylindrical lens) focus the collimated laser beam into a thin laser sheet. The laser sheet

Figure 4. The beginning of the How PIV works learning content page.

After the How PIV Works page, a basic description of the Direct Correlation (DC) method (cross correlations page) provides users with a graphic walkthrough of how the correlation plane is built by shifting one image over the other and finding the sum of the element-wise products. With this understanding of the DC, the Fast Fourier Transform (FFT) Based Cross Correlations page mathematically shows why the FFT is also an estimate of the particle translations (as the DC) and incentivizes this method due to processing speed. To demonstrate how PIV algorithms typically mitigate two primary issues: the balance between windows sizes and output resolution, we also included a description of multi-pass algorithms and sub-pixel estimation. Figure 5 demonstrates a section of the Sub-Pixel Estimation page.



To make a quick fit and avoid allowing the noise around the peak to influence our curve fitting, we apply a Gaussian fit to the three highest points along this ‘cut’ (black) centered around our full-pixel maximum, denoted i. Figure 5 demonstrates the resulting Gaussian curve fit of these three points, and change in r from the full-pixel value of $I = 0$ is the curve peak value, here $I = +0.48$.

Figure 5. The Gaussian curve fit for the $C(r, s)$ points neighboring the full-pixel peak in the r direction. The maximum is at $i = 0.48$, indicating that 0.48 should be added to the full-pixel maximum r.

As we can see from Figure 5, the curve fit provides an estimate of +0.48 pixels from our previous peak. We add this result to the r location of our $C(r, s)$ maximum, to find that the peak is approximately at 5.48 pixels. Remember, the true displacement was $r = 5.5$

Figure 5. A section of the Sub-Pixel Estimation informational page.

These sections describing the basics of PIV provide new users with a fundamental understanding of the processes behind taking images and creating a vector field through PIV. While modern commercial PIV algorithms are much more complicated (even 2D single camera PIV algorithms), this foundation provides an understanding necessary to begin exploring the more complicated aspects of PIV. With the basic understanding of PIV algorithms, however, users should also understand how to gather useful images for processing.

How Imaging Works. To provide an understanding of how to gather useful images, the How Imaging Works section begins with a basic description of digital cameras in the How Does a Digital Camera Work? section. Among the imaging module sections in Table 1, several items such as ISO, bit depth, resolution, shutter speed, and focus are easily compared across a series of images. Figure 6 demonstrates this, in the specific example of ISO.

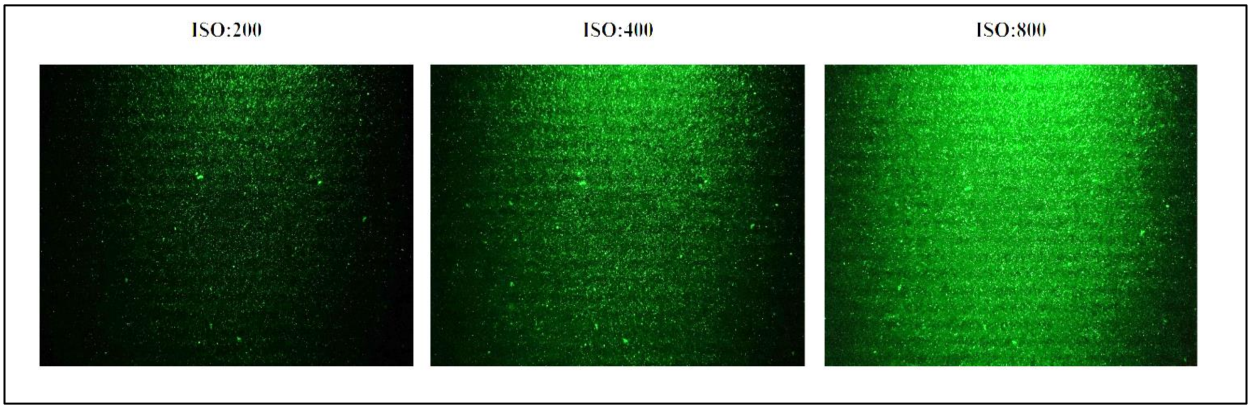
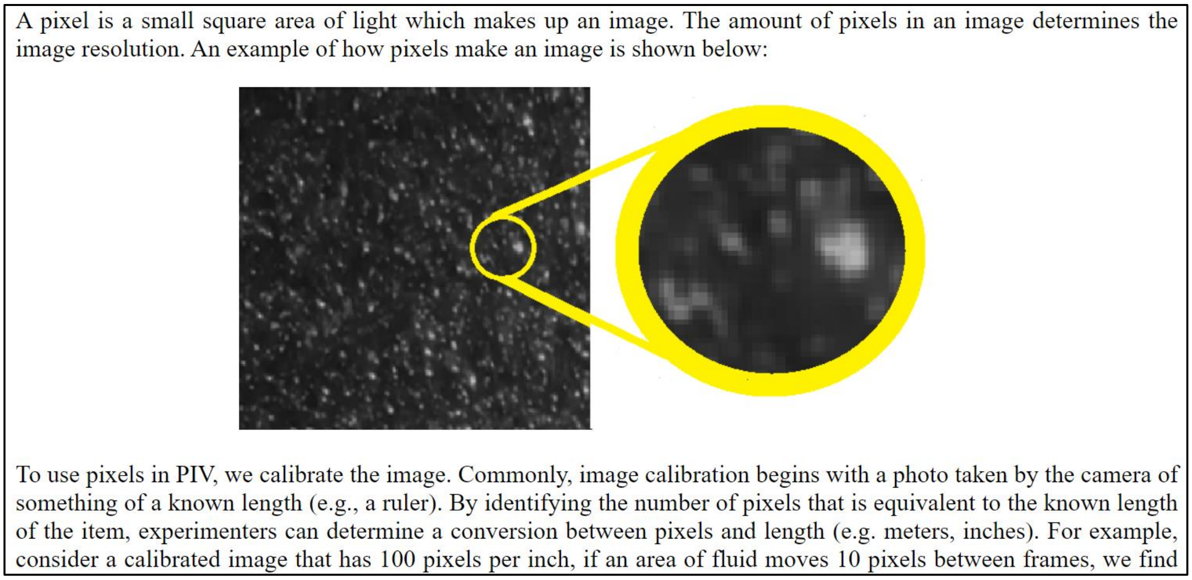


Figure 6. An excerpt from the ISO section of Learn About Imaging, demonstrating the effect of ISO on the brightness of similarly lit images.

For the remaining imaging parameters, the learning content provides a brief description with visual representations. To demonstrate this, Figure 7 provides an excerpt from the Pixel description page.



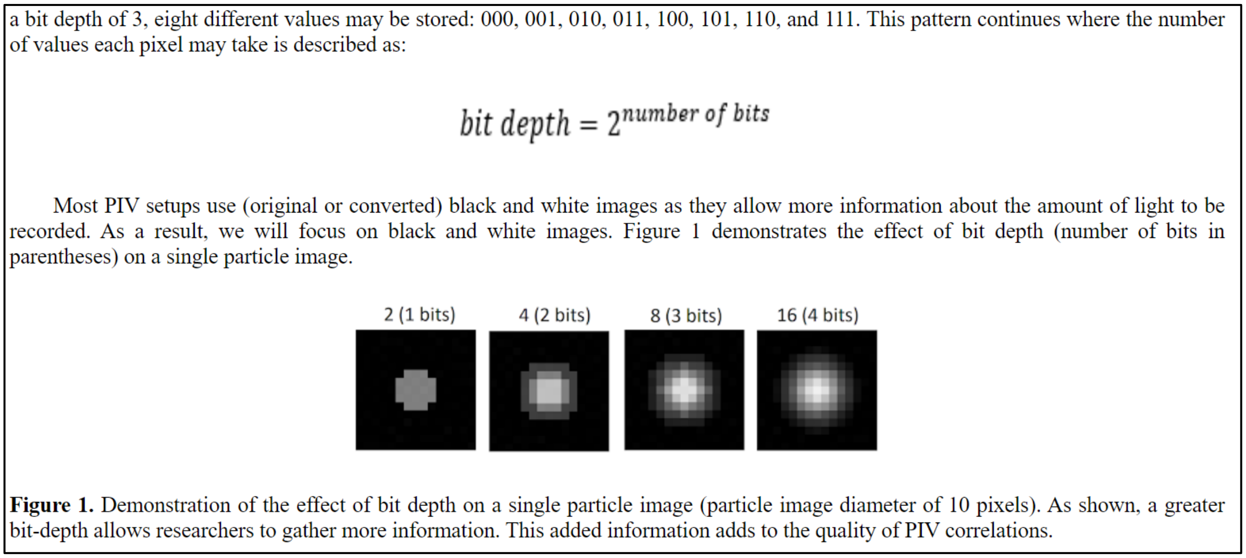
A pixel is a small square area of light which makes up an image. The amount of pixels in an image determines the image resolution. An example of how pixels make an image is shown below:

To use pixels in PIV, we calibrate the image. Commonly, image calibration begins with a photo taken by the camera of something of a known length (e.g., a ruler). By identifying the number of pixels that is equivalent to the known length of the item, experimenters can determine a conversion between pixels and length (e.g. meters, inches). For example, consider a calibrated image that has 100 pixels per inch, if an area of fluid moves 10 pixels between frames, we find

Figure 7. An excerpt from the Pixel learning content in the Learn About Imaging content.

As with the PIV Basics content, the Learn About Imaging material is designed to provide a foundation for early PIV users to build upon. The emphasis on imaging parameters for PIV results provides PIV users with means to understand the importance of critical necessities for achieving accurate PIV results, including providing enough light to image the particles and maximizing the output velocity range.

Synthetic Image Generator Methods. To allow users to effectively interact with the experiment modules and explore the interrogation region scale impacts of varied image and processing parameters, the Synthetic Image Generation learning content provides descriptions of the impact each variable on the synthetic images. To demonstrate, Figure 8 shows an excerpt from the Camera Bit Depth description page.



a bit depth of 3, eight different values may be stored: 000, 001, 010, 011, 100, 101, 110, and 111. This pattern continues where the number of values each pixel may take is described as:

$$\mathit{bit\ depth} = 2^{\mathit{number\ of\ bits}}$$

Most PIV setups use (original or converted) black and white images as they allow more information about the amount of light to be recorded. As a result, we will focus on black and white images. Figure 1 demonstrates the effect of bit depth (number of bits in parentheses) on a single particle image.

Figure 1. Demonstration of the effect of bit depth on a single particle image (particle image diameter of 10 pixels). As shown, a greater bit-depth allows researchers to gather more information. This added information adds to the quality of PIV correlations.

Figure 8. An excerpt from the Camera Bit Depth synthetic image generation learning content.

These descriptions provide a closer look at the impact of the experimental inputs and a visual representation of each parameters' impact on PIV analysis at the scale of the interrogation region. As Figure 8 demonstrates, the user may readily see the influence of bit depth on a particle image. At the scale of the full image (How Imaging Works content), users are less likely to recognize these detailed effects. Thus, the Synthetic Image Content enables PIV users to understand parameters' impacts before (or during) their interactions with the interrogation region scale experimental modules.

Single Variable Experiment

In the Single Variable Experiment module, users can select a specific variable to change across several values, while holding all other values constant. This option enables users to identify the impact of individual variables on the resulting output vector/correlation plane (determined by the FFT-based correlation). For example, to identify the impact of different interrogation region sizes on the output vector, a user may select Interrogation Region Size: "Run Simulations". The synthetic image generator will generate images across Interrogation Region Sizes of 8-128 pixels, allowing users to observe the influence of Interrogation Region Size on the likelihood of the correlation peak being within the correlation plane. An example of this output is demonstrated in Figure 9 with fixed particle displacements of x = 10.2 pixels and y = 5.4 pixels.

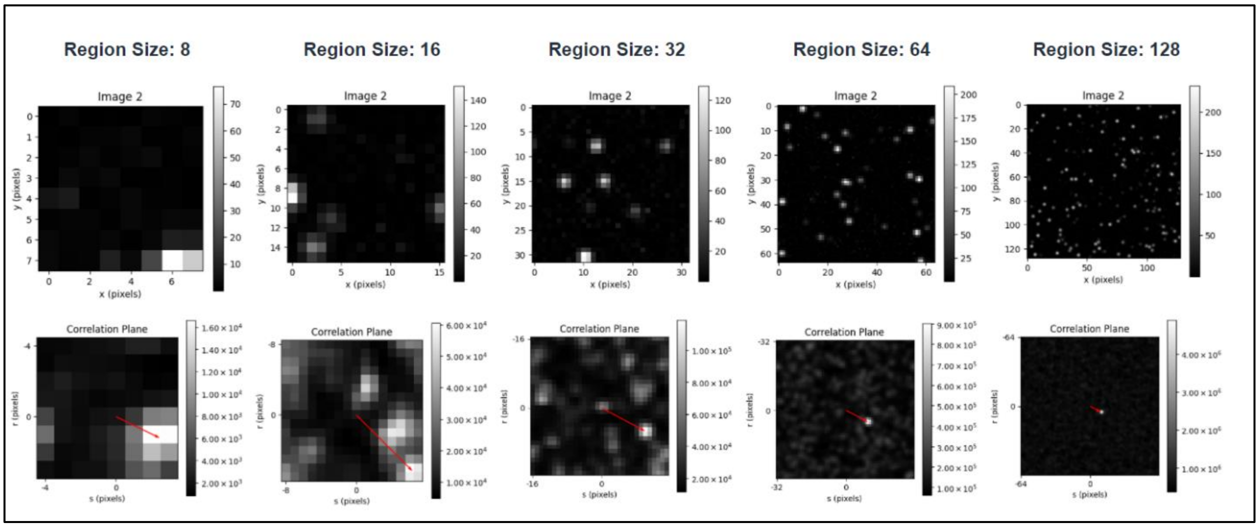


Figure 9. The single variable experiment module results page, providing users with .gif animations of the synthetic images and the resulting correlation plane. This example demonstrates that as the interrogation region size increases, the likelihood of capturing a valid output vector increases.

While the correlation plane results are qualitative and the errors anecdotal, each simulation also provides the histogram of errors (10,000 observations) for each variable value as depicted in Figure 10.

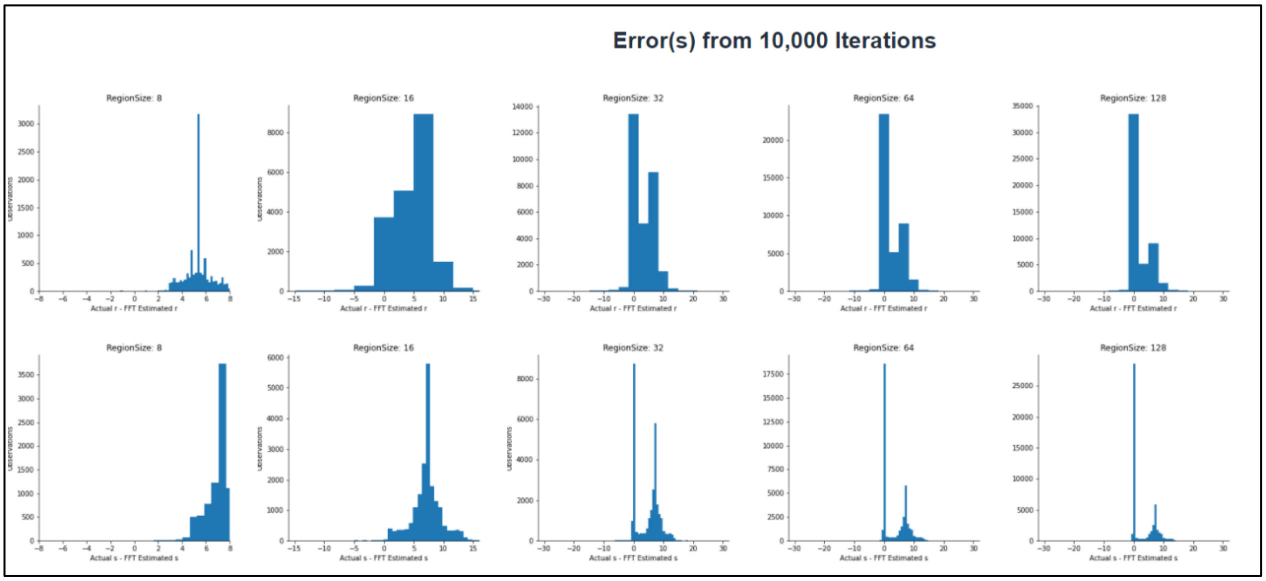
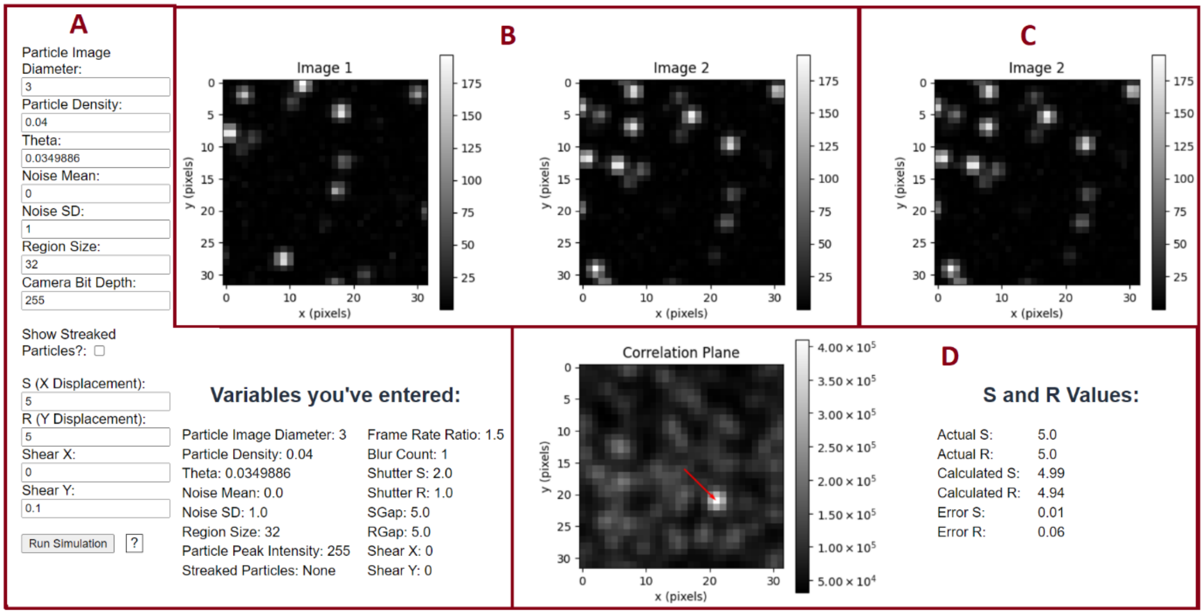


Figure 10. The single variable experiment module results page, providing learners with a histogram of r and s errors for each set of PIV results given each variable value. As demonstrated, the number of vectors with a near zero error (valid vectors) increases as the interrogation region size increases.

The results demonstrated in Figure 10 provide users the ability to understand the influence of the chosen parameter across many observations. For this example, users may see the number of spurious vectors (error >> 0) goes down as the interrogation region size goes up. While these results allow users to vary a single parameter and identify the impact on the correlation plane (and thereby error), experienced PIV users understand that there is a significant coupling between each parameter (e.g., the maximum resolvable particle displacement is approximately ¼ the interrogation region size). To allow novice or advanced users to explore these possibilities and interact in an entirely open manner, we added the Experiment with Multiple Variables Module.

Multiple Variable Experiment

The Experiment with Multiple Variables Module allows LearnPIV.org users to select any combination of synthetic image variables (within the limits of the image generator). After entering these variable values, the LearnPIV.org user selects “Run Simulation”, and the results are provided as demonstrated by Figure 11.



Particle Image Diameter: 3
Particle Density: 0.04
Theta: 0.0349886
Noise Mean: 0
Noise SD: 1
Region Size: 32
Camera Bit Depth: 255

Show Streaked Particles?: ☐

S (X Displacement): 5
R (Y Displacement): 5
Shear X: 0
Shear Y: 0.1

Variables you've entered:

Particle Image Diameter: 3
Particle Density: 0.04
Theta: 0.0349886
Noise Mean: 0.0
Noise SD: 1.0
Region Size: 32
Particle Peak Intensity: 255
Streaked Particles: None

Frame Rate Ratio: 1.5
Blur Count: 1
Shutter S: 2.0
Shutter R: 1.0
SGap: 5.0
RGap: 5.0
Shear X: 0
Shear Y: 0

S and R Values:

Actual S:	5.0
Actual R:	5.0
Calculated S:	4.99
Calculated R:	4.94
Error S:	0.01
Error R:	0.06

Figure 11. The Experiment with Multiple Variables module results page. Inputs are provided in section A, the resulting synthetic image pair is shown in B, with a .gif animating between the two in C, and the resulting correlation plane, vector, and errors in D.

Further, LearnPIV.org users can create an account, and save up to ten of these results at a time. This allows users to change multiple variables and compare their results directly. In all, the experiment with multiple variables page provides PIV users with a means to explore a very broad range of image and processing parameters and consider the results for the correlation plane and resulting output vector.

Future Work

Future work with LearnPIV.org will include continued improvement through user feedback, sustainability efforts, and developing curricula in conjunction with the “mI-PIV” mobile educational PIV app. The current LearnPIV.org tool was vetted through feedback and critique of several experienced PIV professionals/researchers. We have not had opportunity to use LearnPIV.org with an audience of novice PIV users. To identify and resolve any issues with these intended learners, we included a feedback section of the mI-PIV application. This section leads users to a Qualtrics based survey identifying their perceptions of various LearnPIV.org features. The ongoing collection of user feedback will allow us to continually improve this learning tool. Further, we intend to allow users to propose additions and/or edits to the existing Learning PIV content by downloading Word versions of the learning pages and requesting to push their changes/additions to a public (currently private for security) Github repository. Finally, we plan to develop a LearnPIV.org based curricula that will be accessible within the mI-PIV application and published onTeachEngineering.org. These curricula will guide users through several LearnPIV.org experiments as well as assess their achievement of the desired learning outcomes. For example, one curriculum could guide an undergraduate learner through the combined effects of particle displacement and region size to the extent of the learner minimizing region size (to maximize resolution) while retaining valid correlations. These efforts will further deploy LearnPIV.org to engage users who desire a more carefully guided approach.

Conclusions

In summary, LearnPIV.org supports novice (educational and professional) PIV users in learning PIV basics through a variety of means, including static content and dynamic interactive simulation modules. Static content includes information about PIV basics, digital imaging, and synthetic image generation. While this static content provides a basic description of the concepts necessary for PIV data collection and analysis, the Experiment with a Single Variable module enables users to visualize the impact of changing individual parameters on the correlation plane (and uncertainty). To accomplish this interaction, LearnPIV.org provides users with a synthetic interrogation region pair, the correlation plane, and the error distribution for each of five demonstration values across the chosen parameter. To enable learners a completely open experience, the Experiment with Multiple Variables module allows users to generate an interrogation region pair and view the correlation plane and resulting error. The combination of these modules, LearnPIV.org provides engineering students and early professional engineers a means to reduce their time to competency for collecting PIV data and producing useful PIV results.

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