MULTIPHASE ENERGETIC EXPERIMENTS

Application of Multiple Object Tracking

Abstract

The process of using computer vision for multiple-objects tracking is incredibly complex. Thus, simulated data was created to mimic the complexities of more realistic data. These test cases would isolate a few of the inaccuracies of real data and allow the researchers to determine what factor of said data is the most detrimental to the object-tracking process. Due to the large quantity of factors at play, Cotter's method was used to analyze the significance of each factor. The number of detections and the number of centroids were the main dependent results that were utilized to analyze the data. The overall results show that the most significant detriment of successful object tracking is a lack of data in quantity. Additionally, the results show that if particles move too fast for proper imaging, the resultant data is inaccurate. In the future other methods of particle detection should be explored, as currently Kalman filtering is not a viable option for multiphase energetic experiments.

Keywords

computer vision, Kalman filtering, multiphase energetics, Cotter's method, multiple-object tracking, statistical analysis

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Mentors

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experimentation and creating novel reactive materials. His research also seeks to develop or apply the most advanced diagnostics in the harsh reacting environments of energetics to develop improved understanding and characterization. In addition, his research seeks to develop tailored disruptive energetic materials with unique properties. Ultimately his research aims to improve the performance, safety, and toxicity of energetic materials.

MATEO GOMEZ is a current student at Purdue University pursuing his PhD in mechanical engineering. He specializes in using diagnostic techniques to quantify energetic reactions and using computer software to model and process data.

Gomez's previous research is not limited to but includes being able to visualize detonation dynamics and using lasers to track the particles and gases for multiphase blast fields.

INTRODUCTION

In the modern world, multipurpose chemicals that can react energetically (explosively) are unavoidable. Recently in Beirut, more than 200 people tragically lost their lives over a shipment of ammonium nitrate (Orellana, 2021). Ammonium nitrate is a common chemical used in fertilizer and antibiotics, but the material can also be used to create energetics. Unfortunately, if the ammonium nitrate was handled properly, this disaster could have been prevented. When working with energetic materials, or materials that contain a large amount of energy (such as explosives and pyrotechnics), one false move could cause a similar international tragedy. Thus, the best method for preventing these tragedies is to understand and quantify these energetic reactions.

Kalman filtering could help improve our understanding of energetic flows and thus revolutionize how we handle energetic materials and improve overall safety. Kalman filtering is a statistical approach for estimating a value when given a set of data points (Welch & Bishop, 2001). This method has its roots in statistical modeling but has been used for many other applications. Kalman filtering will be utilized in this research to estimate where particles are moving if they are no longer seen in frame. When Kalman filtering is applied correctly, it is easily able to track and predict the movement of a simple object in space. Traditionally, the study of Kalman filtering has mainly been focused on the autonomous systems industry (such as self-driving cars and robotics systems). This essay seeks to apply this well-studied method of estimation to the particle movement of energetics.

METHODOLOGY

This investigation was initially conceived as a method of data processing for a different experiment involving the RP-503 detonator. RP-503 detonators are small exploding bridgewire detonators that utilize small amounts of high-melting explosive and pentaerythritol tetranitrate to create a multiphase energetic reaction (which for the purposes of our research were used to create a small explosion). The initial goal of these experiments was to combine the same background-oriented schlieren (BOS) techniques (a technique used to measure the distortions of a known background to map solid and gaseous

FIGURE 1. (A) Schlieren imaging highlighting particles leading a blast wave and generating bow shocks. (B) 2 MHz schlieren time series of an RP-503 detonator.

movement) from previous experiments and advanced image-processing techniques to generate 3D shock fields and solid phase particles. This involved the necessity to measure both phases of the detonation. Simultaneous measurements of both phases are incredibly difficult and normally require two diagnostic techniques. Figure 1 highlights 2 MHz schlieren videos of an RP-503 detonator that exhibits extensive multiphase flow dynamics. These images were captured on an HPVx2 Shimadzu camera with a 105mm Nikon lens.

If a BOS system is implemented, the hypersonic explosively driven particle shadows can be seen. These images are similar to those obtained from shadowgraph diagnostic techniques. In addition to these images, when a BOS background is utilized, additional information about the shock structure can be obtained because of the imposed frequency of the background. Thus, the experiment utilized such a background and was able to obtain some amount of data relating to the particle movements in space.

In order to obtain meaningful measurements of each phase, the solid phase shadowgraph must be separated from the background data. Thus, a deep exploration into Kalman filters was undertaken to characterize its feasibility to the application in this scenario. If the Kalman filtering proved to be a useful tool, then the particle movements could be isolated over the course of the energetic reaction. In classical Kalman filtering, it was well known that the application worked well in a single particle application. The key problem in this case would be to implement the Kalman filtering on energetics data with numerous particles in a nonideal environment.

The Kalman filtering exploration was implemented using the MATLAB multiple objects tracking software as a base. The program was modified to provide the results for the number of detections and the number of centroids that the program creates. To prove this aspect of the program was accurate, a simple video animation was used to test these modifications (Figure 2). The results clearly demonstrate that the program would output the correct detections and tracking when applied to a known simple test case.

After the Kalman code was modified, the final data was processed to determine how feasible the tracking would be without data preprocessing. If consistent problems were discovered and isolated, the data could theoretically undergo some preprocessing before using the Kalman filtering. From these initial results, it was apparent that there were many variables that made the data differ from a more ideal case. Thus, the researchers created simulated data to isolate known issues with Kalman filtering. As a baseline, the researchers quantified a so-called ideal case where three large solid black circles moved over a solid white background over the course of 28 frames (as shown in Figure 3a). This is the ideal case, as the contrast between the particles and the frame is at its maximum, and the particles go at a steady pace across the frames (no disappearing, hopping, or other irregularities).

In the current study, several parameters were chosen to mimic the energetic data in order to deviate from the ideal case. The first parameter chosen as a relevant factor was the size of the frame. It was hypothesized that the typical smaller frame sizes of energetic data sets available may be contributing to the inaccuracies of the results. Thus, two additional frame sizes were utilized along with

FIGURE 2. A basic example of Kalman filtering detection to prove that the methodology of the code modifications are accurate.

FIGURE 3. (a) Default time series of three simulated particles traversing through the field of view. (b) Modified time series with each row highlighting a different alteration to the default data to approximate possible experimental sources of noise. In order, from top to bottom, are intensity variation, high-frequency background needed for BOS, low-frequency noise, and smaller particle size.

the base frame size. The ideal data has a 600- by 800-pixel size, and the smaller frame sizes are 250 pixels by 400 pixels and 125 pixels by 200 pixels. These numbers were chosen because an entire quad scope for a phantom camera captures data in a 250 by 400 configuration, a quadrant of such quad scope being 125 by 200 pixels. The original data was a 600- by 800-pixel resolution, which dictated the original frame sizes.

The next parameter for consideration was the intensity over time. For the light source in many energetic tests, a class 4 laser is vital. Class 4 lasers over time decrease in intensity, which can cause a decrease in the contrast of the frames. This factor was hypothesized to be a cause of the inaccuracies in the resultant data due to the decreased contrast. So as to mimic this decreasing intensity over time, the base data was multiplied by a scalar fraction that increased every frame. This caused the solid white background to darken over time, which decreased the contrast.

The next notable factor of difference between the test case data and the ideal scenario is the composition of the background itself. In actual data with energetic materials, the images captured from the camera are backgrounded by a target image. In many cases this target image is a calibration image and typically contains a repeating pattern. It was hypothesized that the areas of less contrast in a typical repeating pattern might cause false detection or faulty data. For this test case the repeating pattern of a checkerboard was overlaid in the background to mimic this potential concern.

The next potential discrepancy that may cause data errors is the presence of the quad scopes shadow. The quad scopes' presence in an energetic setup creates a plus-shaped shadow that radiates through the data. It was hypothesized that in a similar way the reduced contrast over time may lead to false results, that is, the areas of reduced contrast may cause the program to struggle in the determination of the locations of the particles.

An additional parameter of interest was the actual length of the video itself. A shorter video has less data to process, which may cause lackluster results. Thus, two different test cases were created to test the potential impact of this parameter on the data. The first test case eliminated every other frame to simulate a lack of data and faster-moving particles. The second test case

replaced every other frame with a blank frame to simulate the faster-moving particles without simulating the lack of data. Once all the parameters of interest had been decided, the various scenarios could be created. These modifications to the default video were applied one at a time (as shown in Figure 3b) or in conjunction resulting in almost 400 trials.

The last few parameters all dealt with modifications to the presentation of the particles to the filtering program. Theoretically, the captured stat could have a warped perspective. This can cause the particles to appear deformed and move in nonideal ways, which may cause irregularities in the final data. Another noteworthy potential factor that was tested for was the size of the particles themselves. Smaller particles were theorized to be harder to track for the computer vision software. Finally, if the frame had any sort of noise present (such as particles not of interest, camera data-collection errors, etc.), then it was theorized that there may be an issue with the particle-tracking software.

Creating these test cases involved first creating the default case and modifying it through MATLAB to meet the desired output. The initial ideal case was created using a simplified animation program, where the spheres stayed a constant size. Then in MATLAB, the video animation was broken into separate tiff images using the `imread` function. Each frame then had the appropriate distortions placed on it depending on what was needed for the data set. The easiest modifications to make were resizing, noise, smaller particles, and warping. To resize the frames the `imresize` function was used, to add noise the `imnoise` function was used (with a specified modification to make the noise Gaussian), to reduce the particle sizes `imdilate` was used, and to warp the `imwarp` function was used. To add in the checkerboard background, the rewritten checkerboard function was used to create a checkerboard of equal size to the frame. Then a for loop went through the data points of the frame and added in the checkerboard pattern to the background. The data was multiplied by 1—the current frame number/total frame number—to create the simulation of a decreasing intensity over time. This would decrease the intensity by a linear amount until the final frame, where there would be no intensity. For the frame removal and replacement method, the method is nearly identical. The code is designed such that if the frame number is even, it

replaces the frame with an empty frame or deletes the frame. Finally, for the quad scope shadow simulation the code defines a function z , which is a function in the form of an ellipse. Then the MATLAB code performs an `fftshift` (which is a MATLAB function to shift zero data to the center of the array) with the function z to get the basic shape of the shadow. Finally, the code elementally multiplies z by the frame to add in the shadow.

Each test case was run through the same multiple object processing that utilized Kalman filtering. The number of detections and the number of centroids were recorded in Microsoft Excel, and each data point was compared to the control test to calculate a percent difference. As the goal of the experimentation was to determine the significance that the source of error was impacting the data, a statistical method called Cotter's method was implemented. Cotter's method is a "sensitivity analysis method used to rank model input parameters" by their impact on the model (Robertson, Zañartu, & Cook, 2016). This approach uses a "two-level" design where all the factors of interest are put at "the high or low extremes" (Robertson

et al., 2016). Because this statistical method is traditionally utilized in the medical industry due to the vast bulk of data and the simplicity of the model, it was determined to be an optimal method for this data analysis. For the frame removal method, complications were introduced in the Cotter's method analysis, as each resized frame could only exist in one of two discrete sizes not simultaneously. In addition, as both the frame removal and replacement methods impacted the even frames of the image, they too could not exist simultaneously with each other. Thus, these factors (removal, replacement, and resizing) could not be combined into a single test case. Because this is a prerequisite for doing a Cotter's method analysis, two separate Cotter's method analyses were used instead for the relevant factors.

RESULTS

When each test case was run through the multiple object tracking algorithm, the results were irregular and lacked a clear pattern (Figure 4). The only trend that was evident

FIGURE 4A. Plots of the number of detected centroids and number of tracks for each of the trials of the simulated data with added experimental noise sources. Data with frame replacement.

FIGURE 4B. Plots of the number of detected centroids and number of tracks for each of the trials of the simulated data with added experimental noise sources. Data with frame removal.

without statistical analysis was that the program failed to detect any objects and perform the Kalman filtering when frames were replaced or left off. However, the other data points needed to be run through Cotter's method before any definitive conclusion could be reached.

Overall, the Cotter's analysis of the test cases showed a few clear factors that impacted the computer's ability to track the objects. From the Cotter's method analysis, reducing the available data via the frame replacement method is the most paramount factor that could affect the computer's ability to track the necessary pathways. When the significance of the track's detection was averaged with the significance of the centroid detection, the overall percentage of significance was 40.9%. With eight factors being a part of each Cotter's method analysis, the base percentage is 12.5%. The available data when reduced is significantly larger than the base percentage, which means this factor impacts the data to a large degree. Out of all the tests this factor had the highest average significance; therefore, it is likely the

most impactful variable. The second most significant factor was found to be the other simulation of a lack of data and faster particle speeds (which was modeled by removing frames). With a significance value of 35.5%, this is shown to be a significant factor when implemented. Thus, a smaller number of frames with usable data and/or faster-moving particles causes inaccuracies to the tracking algorithm. Finally, the size of the particle is not an important factor to the tracking capabilities. With an average significance value of both 0% and 8.2%, this factor had the least significance out of the other notable factors. The other factors that were analyzed had mixed results across the two different analysis and are relatively insignificant (with values ranging from 20% to 12%, indicating close to a base-line significance).

CONCLUSION

In future applications of Kalman filtering, it is evident from the data that there are many factors that will not

affect the overall results of the data (such as noise, warping, variable intensity, particle size, frame size, background patterns, and foreground patterns such as shadows). Thus, if data sets contain similar irregularities, Kalman filtering could be considered for the data processing. However, if any particles come in and out of focus or quickly in and out of the frames, detecting them will likely be difficult due to the high speed and lack of data. This is especially detrimental to the usage of Kalman filtering for energetics data, as the capacity of the camera used for this experiment has a recording capacity of 256 frames saved to memory (Shimadzu Corporation, 2018). While other cameras could be utilized this would not solve this issue, as the energetic data is at such a high speed that obtaining a large frame rate for the small duration is not practical. Thus, this limited frame capacity sets a hardtop on the quantity of data that can be obtained for similar reactions.

Overall, it is evident that the quantity of data and the relative speed of the particles in question are the factors that are the most pertinent. To ensure good results, the camera in question should have a high enough frame rate to capture the particle in a good enough relative speed for detection. However, these parameters are limited for the current set of simultaneous measurements highlighted in the previous reporting period. A larger field of view or faster repetition rate would result in a lack of signal. Therefore, the current implementation of Kalman filters is not a viable solution to the solid phase tracking of the simultaneous experiments.

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