24-036

Estimating Air Blast Velocity Using Optical Flow Algorithm

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ABSTRACT

Large-opening underground stone mines pose significant ground control challenges, including the risk of massive pillar collapses. These collapses can result in dangerous air blasts characterized by tremendous force and high velocity. Estimating the velocity of these air blasts proves challenging due to the absence of accurate air velocity instruments near the mine portals. To address this issue, this paper proposes a novel approach that leverages closed-circuit television camera footage from the mine. Specifically, it employs the optical flow algorithm implemented in Python to estimate the velocity of the air blasts, providing a valuable tool for assessing and mitigating risks in such mining environments.

INTRODUCTION

Underground limestone mines are generally mined using the room-and-pillar method. As the name suggests, the method involves forming a grid-like pattern of entries and crosscuts underground, and the stone deposit is divided into a series of pillars, which are left standing to support the roof of the mine. The method is specially challenging in stone mines as the entry sizes are very large ranging from 40–50 ft wide and 30–40 ft high entries. In addition to the entries, the underground stone mines also use benching. Benching involves further excavating the floor of the entries which increases the development height to 90–100 ft (Figure 1). Therefore, benching creates tall slender pillars in the underground stone mines which are high, but less wide (Figure 2). These pillars often form an hourglass shape and can collapse if the pillar cannot take the weight of the roof (Mark and Rumbaugh, 2022).

A pillar collapse happens when an array of pillars fails suddenly. Pillar collapses can occur with very little warning and can affect miners far away from the collapse (MSHA, 2023). Several factors can contribute to a pillar collapse, including excessive mining of adjacent rooms leading to increased stress on the pillars, geological faults or weaknesses in the surrounding rock, changes in the stress distribution within the mine due to excavation activities or subsurface factors, and inadequate pillar design or insufficient pillar size for the load they are supporting.

Figure 1. Typical large-opening stone mine with benching

Pillar collapse in underground stone mines presents a grave safety concern, as it endangers the lives of miners working not just in the affected area but everywhere near the mine. The sudden failure of support pillars can lead to catastrophic events, including roof collapses and falling debris, placing miners at immediate risk from the ground control event. The pillar collapse also leads to the formation of an air blast.

Figure 2. Hour-glass shape of pillars left after benching

An airblast by definition is a rapid displacement of large quantities of air, often under pressure, caused by a fall of ground in a constrained underground environment. This phenomenon is frequently marked by notable overpressure and high air velocities, carrying the potential for causing fatal harm to individuals and substantial damage to equipment and infrastructure. The severity of the outcomes associated with an airblast is contingent upon the quantity of compressed air involved and the speed at which this compression occurs (NSW, 2006). The miners that are in the high-velocity pathways are at the most risk from an airblast.

Since October 2020, there have been four significant pillar collapses documented in limestone mines, each accompanied by a substantial air blast and the subsequent formation of sizable surface sinkholes (MSHA, 2023). In 2015, a massive pillar collapse resulted in three miners sustaining severe injuries due to the forceful air blast (Rock Products, 2015). It's noteworthy that all these incidents transpired in locations where floor mining, or benching, had significantly heightened the pillars' height (MSHA, 2023). Furthermore, three out of these occurrences took place in "legacy" zones, where mining activities had concluded many years ago.

Therefore, further research into the air blasts is critical at this juncture of time. From a safety point of view, knowing the velocity of an air blast is critical for assessing the potential danger it poses to individuals in the vicinity. High-velocity air blasts can cause injuries, including traumatic impacts and the displacement of people and objects. Understanding the velocity helps in determining safe distances and designing protective measures. In research and safety evaluations, knowing the velocity of the blast wave is essential for characterizing its behavior. This includes understanding how the blast wave propagates, how it interacts with obstacles, and how it dissipates over distance. This information is vital for predicting the extent and severity of blast effects. Calculating the velocity of the air blast helps in the development of effective mitigation strategies.

2.0 PILLAR COLLAPSE INCIDENT VIDEO

This paper utilizes the pillar collapse from a recent incident. In 2021, a crew of miners at a Tennessee limestone operation heard a series of crashing sounds that emanated from an abandoned area containing more than 40 benched pillars. They evacuated the mine and were waiting outside the mine office when they felt the ground shake. Within seconds they watched as enormous clouds of dust, driven by hurricane force winds, rolled out of the nearby portals (Figure 3).

Figure 3. Still frame from the air blast video (MSHA, 2021)

3.0 METHODOLOGY

The idea behind the methodology to estimate the air blast velocity is by using an air blast video captured during a recent pillar collapse incident. This analysis will employ the optical flow algorithm, a well-established computer vision technique recognized for its proficiency in tracking object motion within video sequences (Stanford, 2023). By implementing this algorithm to process the video data, it becomes possible to accurately trace the displacement of air particles and debris associated with the air blast over sequential time intervals. This analytical approach aims to derive quantitative insights into the air blast's dynamic behavior. The research framework, relying on empirical video data and advanced computer vision methods, offers a rigorous and data-driven avenue for comprehending the intricacies of air blast dynamics within the context of pillar collapse events, potentially contributing to enhanced safety and risk assessment protocols in underground mining and related sectors (Dan et al., 2017).

The optical flow algorithm is a computer vision technique used to track the motion of objects or features within a sequence of images or frames in a video. It is named "optical flow" because it simulates the way we perceive the movement of objects when we observe the world around us. The algorithm identifies specific points or features in one frame of the video and then tracks how these features move in subsequent frames. These features can be edges, corners, or other distinctive points that are easy to follow (Nanonets, 2019).

Optical flow estimates the motion of each feature by analyzing the changes in pixel intensity between frames. It assumes that neighboring pixels in the image move together.

The result of the optical flow algorithm is a vector field, where each vector represents the estimated motion of a feature from one frame to the next. The direction of the vector indicates the direction of motion, and the length of the vector represents the speed or magnitude of motion.

The optical flow methodology is visually explained in Figure 4. In the context of optical flow analysis, it is possible to express the variation in image intensity (I) between successive frames as a function of spatial coordinates (x, y) and temporal parameters (t). This entails the displacement of pixels within the initial image, I(x, y, t), by specific spatial increments (dx, dy) over a defined temporal interval (dt), resulting in the creation of a new image, I(x + dx, y + dy, t + dt) (Beauchemin and Barron, 1995).

The optical flow methodology applications get more complicated if the object that we are tracking is not solid,

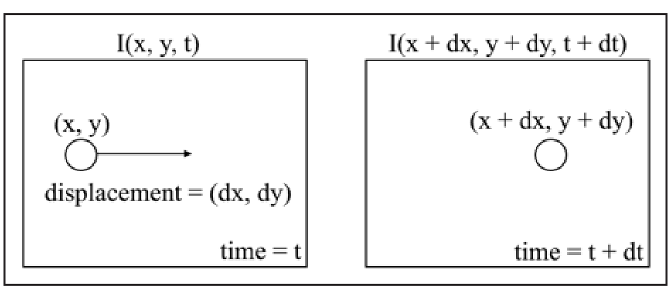

Figure 4. Optical Flow Methodology

meaning the shape is not uniform throughout the motion. This is the case with tracking the dust cloud emanating from the air blast. While the fundamentals of optical flow methodology as described above remain the same, the method is further refined by Lucas and Kanade. Lucas and Kanade introduced an efficient approach for motion estimation of distinctive features by analyzing sequential frames in their publication (Lucas and Kanade, 1981). The Lucas-Kanade method operates based on two assumptions. First, the time interval between two consecutive frames is sufficiently small to ensure minimal object displacement. Second, the frames capture scenes with naturally textured objects displaying gradual grayscale variations.

This paper uses the Lucas-Kanade methodology for optical flow estimation using Python libraries developed by Chuan-en Lin (Nanonets, 2019). In order to repeat this methodology for other applications, the readers can use the Python libraries published by Nanonets. The Python code used in this paper is shared in Appendix A.

4.0 RESULTS

The air blast velocity was calculated using the above-described optical flow methodology. Figure 5 below shows some of the frames from the air blast video captured using the closed-circuit television cameras at various timeframes. Overall, the entire air blast dispersed in about 8 seconds, which makes it very dangerous due to the high air blast velocities. In Figure 5 below, there are four columns and three rows. The columns show the frames and data at various time stamps from the air blast at the portal. The rows show different characteristics of the air blast. Row 1shows the actual frame from the video, row 2 shows the vectors formed in optical flow, row 3 shows the velocities of different number of points in the frame. As noticeable in row 2, the area marked in green is the area within the video that is of interest for velocity estimation as this is the area in front of the portal where the air blast is propagated. As shown in the column B, the air blast really propagates fast at just 1 second, the dust cloud is expanding, and the peak velocities at this time were 60–80 mph. In column C, at 2.5 seconds the peak velocity is 120 mph, which is highly catastrophic right in from of the portal entries.

5.0 SUMMARY AND FUTURE WORK

In summary, pillar collapses in underground limestone mines, capable of producing catastrophic air blasts, pose a severe threat to miners. The room-and-pillar mining method along with benching increases pillar height, creating a potential risk of pillar collapse. There have been four significant pillar collapses since October 2020, leading to

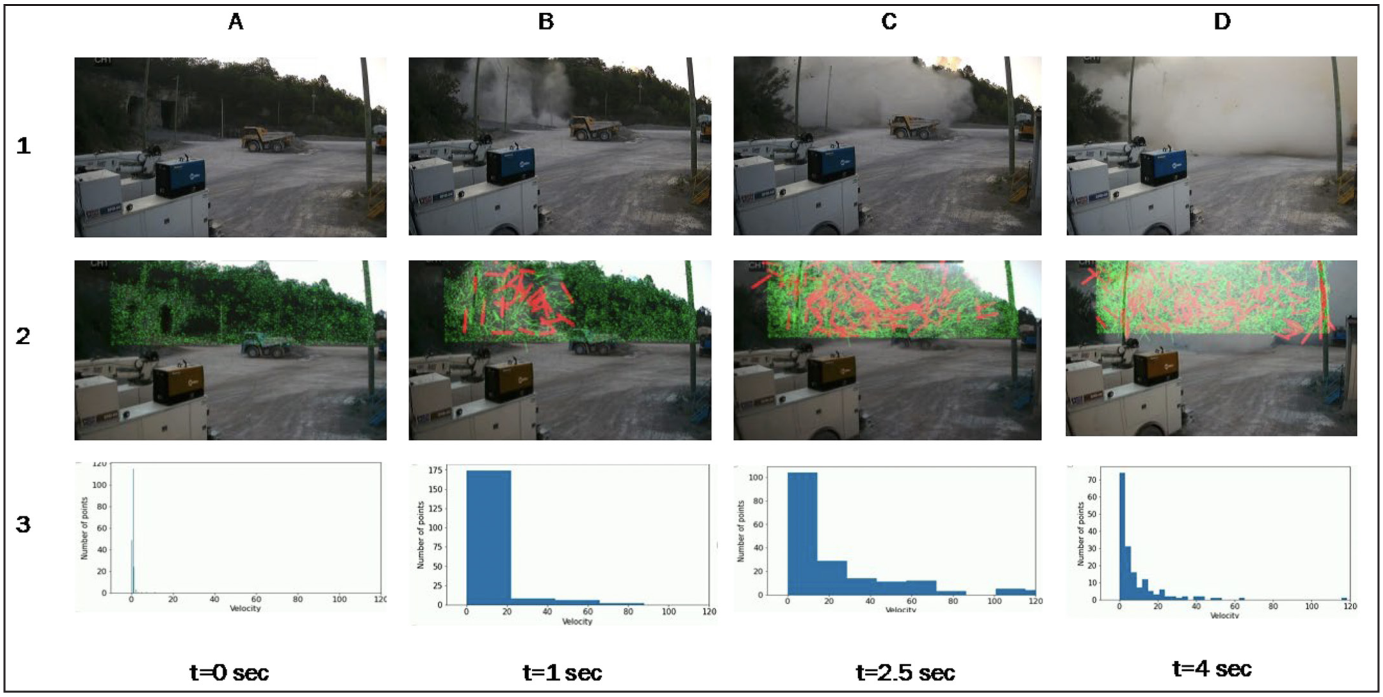

Figure 5. Results from the optical flow algorithm

air blasts and sinkhole formation. The most recent incident in 2021 is described in this paper, emphasizing the sudden and destructive nature of air blasts. The optical flow algorithm is used to estimate air blast velocities by analyzing video footage of pillar collapse incidents. Optical flow is a computer vision technique that tracks the motion of objects or features in video frames, allowing the quantification of air blast dynamics. Results from the analysis of the 2021 incident video reveal rapid air blast propagation with peak velocities of 120 mph within seconds, emphasizing the catastrophic potential of such events.

Proposed future research in this field can be prioritized in several areas. First, continued data collection and analysis of pillar collapses and air blasts are essential to refine safety protocols and mitigation strategies. Additionally, the methods such as developing ventilation air raised in the mines to relieve the air blast pressure should be studied. The above-discussed optical-flow velocity tool currently needs to be run in Python and does not have a graphical user interface; therefore, it requires knowledge of computer coding to use it. In order to make this tool more user friendly, a software is planned to be developed by NIOSH researchers so that users without coding knowledge can use the tool by just uploading a video and calculating the velocity of interest.

Furthermore, research efforts through other sections of the National Institute for Occupational Safety and Health (NIOSH) are being carried out to protect miners from imminent pillar collapses and air blasts. Overall, ongoing research in this field is imperative to safeguard the lives of miners and reduce the risks associated with pillar collapses and air blasts in underground stone mines.

6.0 LIMITATIONS

The work completed in this study was from an exploratory research perspective to evaluate the ability of using surveillance video data to estimate airblast velocities. The velocities estimated from the video used has not been verified with any other scientific measurement and should not be construed as the actual airblast velocity for the event evaluated. Further research efforts, in more controlled environments, need to be conducted to determine if the advanced methodologies and algorithms proposed in this study can be used towards mine accident investigations.

7.0 DISCLAIMER

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention. Mention of any company or product does not constitute endorsement by NIOSH

8.0 REFERENCES

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APPENDIX A

```
[ ]: import cv2 as cv
     import numpy as np
     import seaborn as sns

     import matplotlib.pyplot as plt
     import matplotlib
     font = {'family' : 'normal',
             'weight' : 'normal',
             'size'   : 15}

     matplotlib.rc('font', **font)
```

```
[ ]: import cv2 as cv
     import numpy as np
     mean_d = []
     output_frames = []
     feature_params = dict(maxCorners = 300, qualityLevel = 0.2, minDistance = 2,␣
      ↪blockSize = 7)
     lk_params = dict(winSize = (15,15), maxLevel = 2, criteria = (cv.
      ↪TERM_CRITERIA_EPS | cv.TERM_CRITERIA_COUNT, 10, 0.03))
     cap = cv.VideoCapture("video2.mp4")
     color = (0, 255, 0)
     ret, first_frame = cap.read()
     prev_gray = cv.cvtColor(first_frame, cv.COLOR_BGR2GRAY)
     mask = np.zeros_like(first_frame)
     counter = 0
     while(cap.isOpened()):

         # ret = a boolean return value from getting the frame, frame = the current␣
      ↪frame being projected in the video
         ret, frame = cap.read()
         if counter < 100:
             counter+=1
             continue
         # Converts each frame to grayscale - we previously only converted the first␣
      ↪frame to grayscale
         gray = cv.cvtColor(frame, cv.COLOR_BGR2GRAY)
```

```
    N = 300
    prev = np.zeros([N,1,2])
    prev[:,0,1] = np.random.randint(0,500,N)
    prev[:,0,0] = np.random.randint(200,1500,N)
    prev = prev.astype('float32')
    #prev = cv.goodFeaturesToTrack(prev_gray, mask = None, **feature_params)
    next, status, error = cv.calcOpticalFlowPyrLK(prev_gray, gray, prev, None,␣
↪**lk_params)
    good_old = prev[status == 1].astype(int)
    good_new = next[status == 1].astype(int)
    for i, (new, old) in enumerate(zip(good_new, good_old)):
        a, b = new.ravel()
        c, d = old.ravel()
        dis = np.sqrt(((a-c) * (a-c)) + ((b-d) * (b-d)))
        if np.isnan(dis):
            import pdb
            pdb.set_trace()
        if dis > 70 and dis < 120:
            color = (255, 0, 0)
            thickness = 15
        elif dis > 120:
            continue
        else:
            color = (0, 255, 0)
            thickness = 2
        mask = cv.line(mask, (a, b), (c, d), color, thickness)
        frame = cv.circle(frame, (a, b), 3, color, -1)
    output = cv.add(frame, mask)
    prev_gray = gray.copy()
    prev = good_new.reshape(-1, 1, 2)
    if good_new.shape[0] == good_old.shape[0]:
        distance = np.sqrt(((good_new[:,0] - good_old[:,0])* (good_new[:,0] -␣
↪good_old[:,0])) + \
                    (good_new[:,1] - good_old[:,1]) * (good_new[:,1] - good_old[:
↪,1]))
    else:
        distance =np.zeros([10])
    avg_dist = (np.round(np.mean(distance),2))
    mean_d.append(avg_dist)
    output_frames.append(output)
    values, velocity = np.histogram(distance, bins=40)
    sum_c = np.sum(values)
    values = list(values)
    values.append(N-sum_c)
    values = np.asarray(values)

    fig = plt.figure(figsize= (20,5))
```

```python
    plt.subplot(1,2,1)
    plt.imshow(output)
    plt.title('Average velocity: '+  str(avg_dist))
    plt.locator_params(axis='x', nbins=4)
    plt.locator_params(axis='y', nbins=4)
    plt.subplot(1,2,2)
    #plt.hist(np.ravel(distance), bins=40,histtype = 'bar')
    sns.displot(distance, stat = 'density')

    #plt.bar(velocity, values, 8)
    plt.ylabel('Number of points')
    plt.xlabel('Velocity')
    plt.xlim([-10,120])
    plt.savefig('temp/'+str(counter) + '.jpeg', bbox_inches='tight')
    plt.show()
    counter +=1
    if counter > 450:
        break
cap.release()
```

[ ]:

```python
import cv2
import os

image_folder = 'temp'
video_name = 'video_result.avi'
images = []



frame = cv2.imread('temp/0.jpeg')
height, width, layers = frame.shape

video = cv2.VideoWriter(video_name, 0, 1, (width,height))
for i in range(0,450):
    current_file_name = 'temp/'+ str(i) + '.jpeg'
    video.write(cv2.imread(current_file_name))

video.release()
```