PIWIMS: Physics Informed Warehouse Inventory Monitory via Synthetic Data Generation

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ABSTRACT

State-of-the-art camera-based deep learning methods for inventory monitoring tend to fail to generalize across different domains due to the high variance of scene settings. Large amounts of human labor are required to label and parameterize the models, making a real-world deployment impractical. In a third-party warehouse setting, supervised learning approaches are either too costly and/or inaccurate to deploy due to the need for human labor to address the diverse set of environmental factors (i.e, lighting conditions, product motion, deployment limitations).

We introduce *PIWIMS*, a realistic synthetic dataset generation technique that combines the physical constraints of the scene in real-world deployments, drastically reducing the need for human labeling. In contrast to other generative techniques, where the generative parameters are learned from a large sample of available data, this compositive approach defines the parameters based on physical characteristics of the particular task, which requires minimal human annotation. We demonstrate *PIWIMS* performance in a 4-month real operating warehouse deployment and show that with only 32 manually labeled images per object, *PIWIMS* can achieve an accuracy of up to 87% in inventory tracking, which is a 28% increase when compared to traditional data augmentation techniques and 31% error reduction when compared to the third-party warehouse industry average. Furthermore, we demonstrate the ability of *PIWIMS* to generalize across different camera angles and positions by achieving an accuracy of 85% in inventory tracking while varying the position and angle of the camera.

CCS CONCEPTS

• **Computing methodologies** → **Image representations; Physical simulation; Scientific visualization.**

KEYWORDS

Synthetic Dataset, Computer Vision, Real World Deployments, Product Recognition, Inventory Monitoring

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1 INTRODUCTION

The publication of large-scale object recognition datasets has enabled an unprecedented use of camera-based systems using deep learning. While supervised learning approaches have shown success in classification, detection, and segmentation, these, however, fail to generalize well in the absence of large-scale labeled datasets [18]. Particularly in inventory monitoring applications where a large number of specific objects – e.g. products in retail store, products flowing in and out of a warehouse; and a vast diversity of task-specific environmental factors are present (see Figure 1). Such applications require immense human labor to label data and parameterize the model, making it impractical for real-world adoption.

In order to address this issue, recent techniques, such as domain adaptation techniques [25], data augmentation [19], incremental learning [27], few-shot learning [14] and automatically labeling techniques [17], have appeared to reduce the amount of human labor required in order to adapt the learned models to the domain and data distribution of the specific application. Synthetic data generation aims at creating a large dataset out of a very small

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Figure 1: Typical warehouse setup with forklifts moving the pallets in and out. Diverse set of environmental factors are observed: motion specific to forklifts, camera angle limitation, varying lighting conditions impacted by the weather.

amount of labels by varying characteristics of the original labeled sample. While this allows the trained model to become robust to such variances, it will further over-fit to the patterns in the augmentation itself.

In this work, we present *PIWIMS* which explores different ways of generating synthetic warehouse datasets by leveraging physical knowledge of the deployment setup and object through compositing augmentation to bind the generative parameters closer to the physical reality with minimal human annotation. Our contributions are as follows:

- (1) We propose a new generative data-augmentation technique *PIWIMS*, which leverages physical information –scene lighting, camera position and angle, and object motion, size, and shape– to generate datasets that more closely resemble the deployment data distributions with minimum human annotation labor.
- (2) We present an analysis of a 4 month deployment of *PIWIMS* used in a real world warehouse inventory monitoring system.
- (3) We demonstrate the ability of *PIWIMS* to generalize across camera deployments with varying position and angle.

The remaining paper is as follows: Section 2 describes in detail our approach. Section 3 presents the experimental results and analysis of *PIWIMS* in real-world warehouse setting. Section 4 shows previous works on data augmentation techniques and learning with limited labeled data. Finally, we conclude in Section 5.

2 PIWIMS OVERVIEW

PIWIMS takes inspiration from the ability humans have to look at an image and project different placements for objects of interest. To project an object to a different place in an image, humans have to have a rough understanding of the physical layout of the scene (where the floor is, natural orientation of the object, sources of light, natural motion). This rough understanding of the physical context of a scene is designed into our approach.

Like other compositing techniques [7, 22], *PIWIMS* requires as input a background image, b , and a target image crop, c . Our approach requires as well a linear transformation function, T , and a color correction function, M , and finally applies an alpha blending technique [10] to compose the positive training case. The approach focuses on constraining the parameters of T and M closer to the bounds of physical possibility, while still exploring a larger data distribution. In the simplest case, the final training image is then computed by: $i = b \oplus M(T(c))$ (where " $\oplus$ " corresponds to the alpha blending). However, we can consider multiple c 's and end up with the following formulation:

$$i = b \oplus M_{x_1}(T_{y_1}(c_1)) \oplus M_{x_2}(T_{y_2}(c_2)) \dots \oplus M_{x_n}(T_{y_n}(c_n)), \quad \forall x \in \mathcal{M}, \forall y \in \mathcal{T} \quad (1)$$

Note that each M_x and T_y are different color correction and linear transformations respectively.

2.1 Physically informed linear transformation

The linear transformation defined by T in Eq. 1 is further defined by the input parameters (X, θ, s) . X represents the final location of the center of mass of the cropped image (c) in $\mathcal{R}^2$. X can vary randomly to any point in the image. θ however is constrained by the maximum rotation that c can see given the application-specific setup. This is computed manually by placing c in its original background b at the highest/lowest rotation possible. By manually placing the crop c , *PIWIMS* is bounding the space of possible rotations for c . We define the possible set of rotations as $\mathcal{Y}$.

Similarly, the size S of the crop c is equally computed by manually placing c in the original background b . In this case, the annotator will resize the crop to the largest and smallest possible perceived size given the application-specific setup. Once again, bounding the possible sizes of c to the physically reasonable ones. The size of c is defined by the ratio of the area (number of pixels) of the crop c and the area of b , and its possible space is defined as $\mathcal{S}$. Finally $T \in \mathcal{T}$ where $\mathcal{T} = (\mathcal{Y}, \mathcal{S})$.

2.2 Physically informed color correction

When bounding the possible synthetic images in the color space, we focused on lighting. This is formulated through the function M present in Eq. 1. M represents the color space of the c image in HSL (Hue, Saturation and Lightness) space. In order to encode the lighting characteristics (origin, color, and intensity) easily intuited by humans, *PIWIMS* requires the annotator to understand the lighting in the application-specific setup and place the cropped image c in the original background b , and, similarly to subsection 2.1, search for the maximum/minimum hue and lightness value possible. The range computed between the maximum and minimum values define the space $\mathcal{M}$. Our approach ignores saturation based on the fact that c is extracted from the same source that the model will operate in, which already includes the data characteristics of the light sensor. This assumption can further be alleviated to improve the model.

While this is a homogeneous color mapping transformation, we believe that it is possible to enhance this model with a directed lighting source.

Figure 2: *PIWIMS* consists of two steps: randomly sampling a background image and a target crop, selecting the *PIWIMS* approach, and generating the dataset according to the desired physical characteristics of the scene and the object. The generated dataset is used to train the product appearance model that is fed to the Inventory Monitoring System.

2.3 Target Motion

Even though the motion is associated with a continuous set of images (video), it can still be perceived in a static image. Motion blur can be detected in a single image, indicating a natural motion that creates a loss of detail due to the capture rate of the camera's sensor. The same principles applied in Section 2.1 and Section 2.2 can be applied here. Motion blur can be applied by a convolution between a kernel k , defining the direction and intention of the motion, and the image c .

In cases where the ordered series of images is available, motion can further be used through a pre-processing step of background subtraction [20]. *PIWIMS* transforms the background image b using a synthetic background subtraction removal function f . f randomly samples the coordinate space of b and converts that pixel into a black pixel with probability p . In case one of its 8 neighboring pixels has been converted to black its "turning black" probability doubles becoming $(1 + p)/2$. This is defined as such:

$$P(b_{x,y} = 0|p) = \begin{cases} p & , \forall x, y \text{ where } b_{|x-1|, |y-1|} \neq 0 \\ \frac{(1+p)}{2} & , \forall x, y \text{ where } b_{|x-1|, |y-1|} = 0 \end{cases} \quad (2)$$

We have identified empirically that $p = 0.53$ has the best performance when reproducing the effects of background subtraction. See 2c). for an example of a resulting background images with $f(b, 0.53)$.

2.4 Occlusion and Negative Sampling

When blending the background, b , with the multiple target cropped images, c 's, [22] has demonstrated that the artifacts created by composing the final image can be identified by the training model, which leads to it expecting such artifacts in the application-specific images. Therefore *PIWIMS* further adds similarly shaped, to c , extra cropped images denoted as v with content from the different random background, in order to create negative samples with the compositing artifacts. (See Fig. 3). The last step of *PIWIMS* is to remove samples generated with extreme occlusions by applying

Figure 3: The top three images show the effect of random dataset generation that lies outside the physical reality of the application. The bottom three images demonstrate the generation process based on *PIWIMS* linear transformation, color correction and negative sampling.

NMS (non-maximum suppression) with a threshold of 0.8 on the generated c images.

3 REAL-WORLD EVALUATION AT AN OPERATING WAREHOUSE

In this section, we present a component-wise analysis of the different stages of *PIWIMS* and the results of the deployment of *PIWIMS* in a real-world operating warehouse monitoring system. In partnership with ThaiBev, we have deployed a warehouse inventory monitoring system based on the data generated by *PIWIMS*. We analyze in this paper 4-month of operation of this warehouse. And further evaluate each component of *PIWIMS* in Sections 2.1, 2.2 and 2.3 (See Fig. 2).

3.1 Warehouse camera deployment and dataset generation

We deployed two cameras at a ThaiBev's warehouse for varying camera positions and angles. The cameras' placement is chosen in

Figure 4: Detection Accuracy results with IoU = 0.8, using fully synthetic datasets generated using various data augmentation techniques. We show that *PIWIMS* with minimum human labor (only 32 manually labeled images) outperforms the other techniques for both the deployments.

a way to capture the maximum activity occurring at each door. The cameras operated at 15fps and recorded all activities during the four months of the deployment. The deployment was coordinated to record the 4 busiest months of the year. We have further obtained the inventory count from a separate warehouse monitoring system (WMS) for comparison.

Ground truth was generated by manually annotating 35 hours of randomly selected video frames from different days and cameras. We further evaluate the effectiveness of our approach by comparing our visual inventory monitoring results with ThaiBev’s WMS results.

Dataset generation was achieved by extracting 32 cropped product images of the highest selling item in the warehouse from each deployed camera, c_n . We have further leveraged the Indoor Scene Recognition Dataset [13] to generate our backgrounds b for an increased variety of backgrounds which facilitates the generalization process. By following the approach describe in Sec. 2, we create fully synthetic datasets of 30,000 images out of the 32 cropped sampled images (with a 20:20:60::validation:testing:training dataset composition), for each component provided in Sec. 2 (See Fig. 2). We then train a FasterRCNN [15] model with the synthetically generated datasets for the different steps in *PIWIMS*.

3.2 Metrics for Product detection and Product flow counting

Inventory Monitoring requires the vision systems to detect the products of interest and track their flow over time. For this purpose, we have divided our analysis of the results into *Product detection accuracy* and *Product flow counting*.

Product Detection is a localization and classification task, which we evaluate using the F1-score @ 0.8 IoU, that is $\frac{|G \cap P|}{|G \cup P|} \geq 0.8$, where G is the ground truth bounding box and P is the predicted bounding box.

Product flow counting aims to estimate the locations of products in a video sequence and yield their individual inflow/outflow count based on the entrance and exit zone in the warehouse, which we evaluate using the F1 score. If the ground truth states a product

Figure 5: Inventory Count Evaluation Results for different models, using synthetic datasets generated with only 32 manually labeled images. Our approach, *PIWIMS* has an 8% performance increase compared to Albumentations [3] 31% error reduction as compared to WMS (dotted line).

inflow/outflow at time t_1 , and the predicted time states a product inflow/outflow at time t_2 , it is considered a true positive if $|t_1 - t_2| \leq 50$, where we consider 50 frames (equivalent to 3.5 seconds) to accommodate for human annotation errors.

3.3 *PIWIMS* data augmentation performance

In order to evaluate the performance of *PIWIMS* we have leveraged several data augmentation techniques and used them for the warehouse inventory monitoring deployment. We compare our model with Albumentations [3], and various techniques from Keras Image Data Generator [5] on product detection and product flow counting subtasks. The results show that all the components of *PIWIMS* perform better or on-par with the baseline on respective tasks (See Fig. 4 and 5).

Product Detection: Following the approach in Sec.2 we create detection models from the synthetically generated datasets for *PIWIMS*, Albumentations [3] and Keras Image Data Generator [5] methods. We demonstrate in figure 4 that with a minimum amount of human labor (only 32 cropped samples), a combination of all the components of *PIWIMS* achieves 99% F1-score @ 0.8 IoU.

Product Flow Counting: We detect the inventory by running our trained models and then use SORT [26] to track the movement in 2D of the products across time. We further define an entrance and exit zone in the image, determining whether a moving product is considered inflow or outflow. Figure 5 shows that we see an 8% improvement in F1-score for the first camera and on-par performance for the second camera as compared to other data augmentation techniques.

Furthermore, we compare our model with WMS data (See Figure 5), the 3rd party warehouse industry average. The results demonstrated that our models resulted in a 31% reduced error as compared to WMS.

3.4 Generalization across different camera angle and position

In order to demonstrate the ability of *PIWIMS* to generalize across different camera installations, we deployed a second camera at the

Physically informed parameters	Impacted by
Linear Transformations ($\mathcal{Y}$)	Camera angle and position
Color Correction ($\mathcal{M}$)	Lighting angle and intensity
Motion Blur	Warehouse product motion
Occlusion Parameters	Camera position

Table 1: Analysis of physical realities that impact the parameters used for data generation in *PIWIMS*. Notice that, in general, linear transformations and color correction are derived from camera placement motion blur and occlusion parameters are specific to the warehouse characteristics.

same warehouse (see Figure 1). The second camera is deployed at the same height from the warehouse platform as the first camera. As both cameras are deployed in the same warehouse, similar physical information is extracted when generating the synthetic datasets.

In Table 1 we list the factors that impact the physical parameters used in *PIWIMS*. As the second camera is deployed at the same height as the first camera, the linear transformations $\mathcal{S}$ remain similar across cameras. However, the linear transformations $\mathcal{Y}$ is adjusted according to the angle of the second camera. The color space $\mathcal{M}$ for images collected from the second camera differs from the first camera. This occurs since the first camera is installed close to the door with direct sunlight access, but this is not the case for the second camera installation. Motion blur and occlusion parameters are similar across camera installations as they are specific to the warehouse, and the product of interest moves at similar speeds from both perspectives.

Evaluation was done by running the same trained model produced for the first camera on the second camera. We randomly selected 10 hours of video from the second camera, from different days and times of the day of the four months of the deployment. This data was annotated by manually looking at the video and registering how many inflows and outflows of the desired product occurred during this 10 hours period. Figure 4 and 5 demonstrate that *PIWIMS* generalizes well across different camera installations without added human labor for annotation. *PIWIMS* exhibited a 19% improvement on product detection subtask compared to the other data augmentation techniques and on-par performance on product counting subtask.

4 RELATED WORK

There is a significant amount of work in synthetic data generation with the intent of overcoming the burden of labeling large datasets for training neural networks. However, most of these works lack the optimization for the target application and focus on just slightly perturbing the available data distribution. These can be grouped into learning-based image synthesis, photo-realistic mapping and contextual image composition.

Learning-based image synthesis: In order to synthesize positive examples for training object detection models prior works [2, 21, 28] leverage pre-existing labeled datasets and vary its characteristics (i.e. saturation, brightness, orientation, etc.) to augment the data distribution with the attempt at maintaining the patterns that make such an example a positive one. These parameters can be learned by a model to generate these synthetic images [4, 6] or generated through adversarial examples [1, 12, 22]. ST-GAN [10] uses

spatial composition to generate new images, however, without the contextual understanding of the target application. These, however, still require a large available labeled dataset to learn meaningful patterns and generate image samples that improve the training performance.

Contextual image composition: Image composition refers to the technique of cropping separate images and composing them in such a way that new images are generated with, ideally, similar data distribution to the target context. While these techniques [7, 8, 24] have shown an increase in performance through the random placement of images crops on random backgrounds, they tend to generate unrealistic datasets, limiting its ability to adapt to new domains [7]. To improve this, data augmentation techniques have adopted a parameterized method to limit the distribution of the composition [2]. However these parameters require a large amount of human labor to fine-tune its performance for each composition. To address this, prior works use heuristical [8] techniques or contextual cues [11] to improve the realism of the composition.

Photo-realistic mapping: Photo-realistic 3D simulation engines, such as game engines, have recently gained popularity for data augmentation purposes [9, 16, 23]. These approaches provide a large degree of control over the possible transformations done to available data and into the realism of the resulting dataset. However, the significant downsides of this approach are the domain gap between simulated images and the real application and the hidden need for human labor to generate and ingest 3D data into the simulator.

5 CONCLUSION

We introduce *PIWIMS*, a physics-informed synthetic data generation technique for real-world deployments. *PIWIMS* utilizes the physical constraints of the environment and the objects to generate realistic datasets. Our approach requires minimal human annotation, and we demonstrate that with an empirical study of inventory monitoring in a warehouse, where we achieve 87% accuracy in inventory tracking with only 32 manually labeled images.

While these results show great promise in deploying a vision system with virtually no available data and with minimal human labor, they are still preliminary. Future work will involve evaluating this approach against an increasing variety of products and an increase variety of deployments. In addition, further exploration is required to understand the minimum required number of manually annotated samples are required to perform well.

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