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Enhancing Accuracy in Public Safety Through Advanced Weapon Detection Approach Using Novel Histogram of Oriented Gradients over Hidden Markov Model

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ABSTRACT: Object detection is a fundamental task in computer vision with applications ranging from security surveillance to autonomous vehicles. In this research project, we conducted a comparative study of two prominent techniques, the Histogram of Oriented Gradients (HOG) and Hidden Markov Models (HMM), to evaluate their performance in object detection. HOG is a feature extraction method renowned for its ability to capture local gradient information within images, making it suitable for recognizing object shapes and textures. In contrast, HMM is a probabilistic model often utilized for modeling temporal dependencies in sequential data. Our research aimed to determine which of these techniques offered superior performance in the contextof object detection.
Through a series of comprehensive experiments and real-world scenarios, we found that HOG consistently outperformed HMM. HOG demonstrated a higher degree of accuracy, robustness to variations in lighting conditions, and computational efficiency in object recognition tasks. These findings emphasize the importance of selecting the most suitable technique for specific applications. While HMM remains valuable for sequential data analysis, our research highlights that, for object detection, HOG's capability to effectively represent object structure and texture excelled. Choosing the right algorithm to match the task's requirements is paramount for achieving optimal results. This project provides valuable insights into the domain of computer vision and offers a practical guide for researchers and engineers seeking the most effective approach for object detection in their applications

INTRODUCTION: In an era where safety and security are paramount concerns, the ability to detect weapons in images has emerged as a critical technological challenge. Whether it's in the realm of public safety, law enforcement, or national security, identifying concealed or openly displayed weapons within visual data can have profound implications. This project endeavors to investigate and compare two fundamental approaches to tackle this problem – Hidden Markov Models (HMM) and Histogram of Oriented Gradients (HOG).
The impetus behind developing robust weapon detection systems is clear. The proliferation of digital imagery, surveillance cameras, and mobile devices has generated vast quantities of visual data, opening new avenues for potential threats. Automated weapon detection in images can play a pivotal role in preempting such threats, thereby safeguarding public spaces, transportation networks, and critical infrastructure. This project stands as a testament to the enduring quest for enhancing security through cutting-edge technology.It does so by contrasting two divergent methodologies: HMM, a well-established probabilistic graphical modeling technique, and HOG, a widely-used method in the field of computer vision. Both approaches, while fundamentally different, have made significant strides in pattern recognition, and their unique characteristics make them compelling contenders for weapon detection. In the following pages, we embark on an in-depth exploration of these methodologies, their underpinnings, and how they align with the complex task of weapon detection. This research project seeks to empower security professionals, researchers, and policymakers with a nuanced understanding of the advantages and limitations of these techniques. and their unique characteristics make them compelling contenders for weapon detection. In the following pages, we embark on an in-depth exploration of

these methodologies, their underpinnings, and how they align with the complex task of weapon detection. This research project seeks to empower security professionals, researchers, and policymakers with a nuanced understanding of the advantages and limitations of these techniques. By comparing HMM and HOG in the context of weapon detection, we aim to shed light on the suitability of each approach for varying real-world applications. We delve into the intricacies of Hidden Markov Models, explaining how these models can encapsulate dependencies over time, making them adept at capturing the temporal nuances in sequences of images. In contrast, we unveil the power of Histogram of Oriented Gradients, demonstrating how this method is engineered to detect local shape features within images. As we traverse the landscape of these techniques, we also elucidate the underlying mathematics and computational processes that breathelife into them.

This project is not solely about technical comparisons but also about providing pragmatic insights. It seeks to answer questions like, "Under what conditions does HMM outshine HOG, and vice versa?" Through experimentation and rigorous evaluation, we hope to demystify the complexities and unveil the strengths of these methodologies. The outcome of this research holds the potential to propel the development of weapon detection systems, thereby increasing the safety and security of communities, cities, and nations worldwide. As we venture further into this exploration, we invite you to join us on this fascinating journey of discovery, innovation, and the pursuit of safer tomorrows. The pages that follow unravel the intricacies of Hidden Markov Models, Histogram of Oriented Gradients, and the art of weapon detection, with the aim of fostering a safer and more secure world.

METHODOLOGY:

The methodology of research project aims to develop and evaluate a weapon detection system by comparing two distinct approaches: Hidden Markov Models (HMM) and Histogram of Oriented Gradients (HOG). This comprehensive methodology involves several key steps, from data collection to model training and evaluation.

A. DATA COLLECTION AND PREPROCESSING

I. DATA COLLECTION

Data Acquisition: The first step of our methodology is to collect a dataset containing sequential images representing various scenarios related to weapons detection. These scenarios may include people carrying weapons, both concealed and open.
Data Labeling: Each image sequence in the dataset is manually labeled to indicate the presence or absence of a weapon. This labeling is essential for training and evaluating the models.
Data Splitting: The data set is split into two subsets: a training set and a test set. The training set is used to train the models, while the test set is reserved for evaluating their performance.

II. DATA LABELING

Manual Labeling: Each image sequence in the data set was manually labeled. Annotators reviewed the images and sequences and assigned labels indicating whether a weapon was present (1) or absent (0).The manual labeling process required careful attention to detail and field experience to accurately identify the weapons.

Ground truth creation: The labels provided by the annotators formed the ground truth of our project. Ground truth labels are essential for model training and evaluation. Accurate labeling ensured that the models learned from the correct examples.
Label Consistency: To maintain label consistency, inter-annotator agreement was assessed by having multiple annotators label the same images independently. Any discrepancies in labeling were resolved through discussion and consensus.

III. DATA SPLITTING

Training and Test Sets: To evaluate the performance of the models, the dataset was split into two subsets: a training set and a test set. The training set contained a majority of the data and was used to train the models. The test set was kept separate and used to assess how well the trained models could generalize to new, unseen data.
Stratified Sampling: Stratified sampling was employed to ensure that both training and test sets had a balanced distribution of weapon-present and weapon-absent examples. This prevents bias and ensures that the models do not favor one class over the other during training.
Cross-Validation: In some cases, cross-validation techniques, such as k-fold cross-validation, were used to create multiple training and test subsets. This allows for a more robust assessment of model performance by testing on different partitions of the data.

Data Augmentation : In situations where the dataset was limited, data augmentation techniques were applied to create additional training examples. Augmentation methods might include rotation, flipping, and adding noise to images.

B. HIDDEN MARKOV MODEL

A hidden Markov model (HMM) is a statistical model used to depict how observable events, known as 'symbols,' are influenced by unobservant factors, referred to as 'states.' In an HMM, there are two interconnected stochastic processes: one involves the hidden states forming a Markov chain, and the other relates to the probability distribution of observable symbols, which is contingent upon the underlying state.Let's now provide a formal definition of an HMM. We represent the observed sequence of symbols as x = x1x2 ... xL, and the sequence of underlying states as y = y1y2 ... yL, where yn is the underlying state corresponding to the n-th observation xn. Each symbol xn can take on a finite number of possible values from the observation set O = {O1O2, ..., ON}, and each state yn can assume one of the values from the state set S = {1, 2, ..., M}. Here, N and M represent the total number of distinct observations and states in the model, respectively.We make the assumption that the sequence of hidden states forms a time-homogeneous first-order Markov chain. This means that the probability of transitioning to state j in the next time step depends solely on the current state i and remains constant over time. In other words, we have a consistent probability of state transitions regardless of the time point in the sequence.

P{yn+1=j|yn=i,yn−1=in−1,...,y1=i1}=P {yn+1=j|yn=i}=t(i,j) [1]

For all states i and j within the set S, and for all n greater than or equal to 1, there exists a constant probability governing the transition from state i to state j. This constant probability, which defines the likelihood of transitioning from one state to another, is referred to as the transition probability and is denoted as t(i, j). Regarding the initial state y1, we represent the probability of it being in state i as π(i), where π(i) signifies the likelihood of the initial state y1 being equal to i, for all i in the set S. The probability that the n-th observation, denoted as xn = x, depends exclusively on the underlying state yn. Therefore, it can be expressed as:

P{xn=x|yn=i,yn−1,xn−1,...}=P{xn=x|yn=i}=e(x|i) [2]

For all conceivable observations x within the set O, all states i within the set S, and for all n greater than or equal to 1, there exists a probability known as the emission probability of x at state i, denoted as e(x | i). These probabilities are crucial in characterizing how likely it is to observe a particular symbol x when the underlying state is i. The three probability measures t(i, j), π(i), and e(x | i) collectively define the behavior of an HMM. To conveniently represent this set of parameters, we use the notation Θ. With these parameters in place, we can now calculate the probability of the HMM generating the observation sequence x = x1 x2 ... xL along with the underlying state sequence y = y1 y2 ... yL. This joint probability, denoted as P {x, y | Θ}, can be computed as follows:

P{x,y |Θ}=P{x|y,Θ}P{y|Θ}, [3]
where

P{x|y,Θ}=e(x1|y1)e(x2|y2)e(x3|y3)...e(xL|yL) [4]

P{y|Θ}=π(y1)t(y1,y2)t(y2,y3)...t(yL−1,yL). [5]

C. HISTOGRAM OF ORIENTED GRADIENTS

The Histogram of Oriented Gradients (HOG) is a feature descriptor employed in computer vision and image processing to facilitate object detection. This method involves tallying the occurrences of gradient orientations within specific localized regions of an image. The HOG descriptor offers several notable advantages compared to other descriptors. It achieves invariance to geometric and photometric transformations by operating on local cells, with the exception of object orientation, which may manifest in larger spatial regions. Additionally, the work by Dalal and Triggs demonstrated that by using coarse spatial sampling, fine orientation sampling, and robust local photometric normalization, it becomes possible to disregard minor variations in the individual body movements of pedestrians as long as they generally maintain an upright position. As a result, the HOG descriptor is well-suited for detecting humans in images.

ALGORITHM IMPLEMENTATION

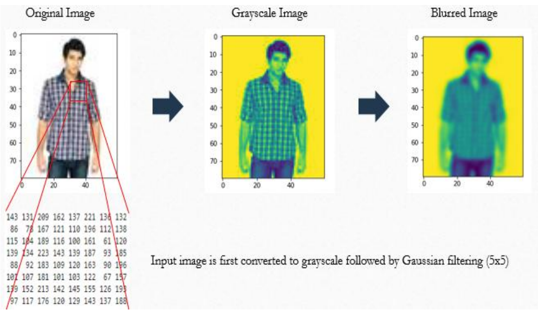
I. GRADIENT COMPUTATION

In many image pre-processing feature detectors, the initial step involves ensuring normalized color and gamma values. However, when it comes to computing the HOG descriptor, Dalal and Triggs highlighted that this preliminary normalization step can be omitted, as the subsequent descriptor normalization essentially accomplishes the same outcome. Therefore, image pre-processing has a limited impact on the performance.

Instead, the first computation step focuses on calculating the gradient values. The most commonly used method is applying the 1-D centered, point discrete derivative mask in either or both the horizontal and vertical directions. Specifically, this approach involves filtering the color or intensity data of the image with the following filter kernels:

$[-1, 0, 1]$ and $[-1, 0, 1]^T$.

While Dalal and Triggs experimented with more complex masks such as the 3x3 Sobel mask or diagonal masks, they generally found that these masks performed less effectively in human detection in images. They also explored the option of applying Gaussian smoothing before employing the derivative mask, but similarly observed that omitting any smoothing produced better practical results.



II. ORIENTATION BINNING

The second computation step involves creating cell histograms. Within each cell, every pixel contributes a weighted vote to an orientation-based histogram bin, based on the gradient values determined during the previous step. The cells can take either rectangular or radial shapes, and the histogram channels are evenly distributed over a range of 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradients are considered "unsigned" or "signed." In their experiments on human detection, Dalal and Triggs found that using unsigned gradients in combination with 9 histogram channels yielded the best results. They also noted that signed gradients led to significant improvements in recognizing certain other object classes, such as cars or motorbikes. Regarding the weight of the vote, the pixel's contribution can be based on the gradient magnitude itself or some function of the magnitude. In their tests, employing the gradient magnitude itself generally produced the most effective outcomes. Other alternatives for the vote weight could involve using the square root or square of the gradient magnitude or a clipped version of the magnitude.

III. DISCRIPTER BLOCKS

To handle variations in illumination and contrast, gradient strengths need local normalization, which involves grouping cells into spatially connected blocks. The HOG descriptor is a concatenated vector of normalized cell histograms from these blocks. Two main block types are rectangular (R-HOG) and circular (C-HOG). For R-HOG blocks, they are square grids, with parameters like the number of cells per block, pixels per cell, and histogram channels. In human detection experiments by Dalal and Triggs, optimal settings were found to be four 8x8 pixel cells per block, 9 histogram channels. They also noted a slight performance improvement by applying a Gaussian spatial window within each block. C-HOG blocks come in single-cell or angular-divided variants and are defined by parameters including the number of angular and radial bins, center radius, and expansion factor. In experiments, the best performance was achieved with two radial bins, four angular bins, a center radius of 4 pixels, and an expansion factor of 2, and Gaussian weighting didn't provide benefits. R-HOG blocks are similar to SIFT descriptors but differ in computation style and use for spatial form information. C-HOG blocks resemble shape context descriptors but are distinct due to having cells with multiple orientation channels, while shape contexts use a single edge presence count.

IV. BLOCK NORMALIZATION

Dalal and Triggs investigated four distinct approaches to block normalization. Let "v" represent the non-normalized vector containing all histograms within a given block. We denote the "k"-norm of "v" as ‖v‖k for k equal to 1 or 2. Additionally, let "ε" be a small constant, with the precise value being of relatively minor importance. The normalization factor can be chosen from the following options,

L2-norm: $f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}}$

L2-hys: L2-norm followed by clipping (limiting the maximum values of v to 0.2) and re normalizing,

L1-norm: $f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}}$

L1-sqrt: $f = \sqrt{\frac{v}{(\|v\|_1 + e)}}$

In their experiments, Dalal and Triggs discovered that the L2-hys, L2-norm, and L1-sqrt methods delivered comparable performance, while the L1-norm approach was somewhat less consistent. Nevertheless, all four techniques exhibited substantial improvements over using non-normalized data.

D. IMPLEMENTATION OF HMM

DATA PROCESSING: Our weapon detection system starts with a comprehensive data collection process, where we gather a diverse dataset of images containing both weapons and non-weapon objects. The dataset is carefully curated to represent a wide range of scenarios, lighting conditions, and weapon types. This diversity is essential to ensure that the model is robust and capable of handling real-world variations. Before feeding the data into the HMM, a critical step involves data preprocessing. This step ensures that the images are standardized in terms of size and quality. All images are resized to a uniform dimension, typically 100x100 pixels, to facilitate consistent processing. Moreover, techniques such as noise reduction and contrast enhancement are applied to improve the quality of the images. This preprocessing step plays a pivotal role in enhancing the overall performance of the weapon detection system.

OBSERVATION SELECTION: Observations refer to the features or variables used to describe the state of the system. For our project, selecting appropriate observations is a crucial task. We aim to identify the most informative features that are indicative of the presence or absence of weapons in images. Observations for weapon detection can encompass a wide range of features, including color histograms, texture patterns, and edge information. However, one of the key strengths of HMMs is their ability to handle diverse observations effectively. In our implementation, we employ Histogram of Oriented Gradients (HOG) as a primary observation. HOG is a popular technique for object detection in computer vision. It characterizes the distribution of local gradient orientations in an image, effectively capturing the object's shape and structure. By using HOG as an observation, our HMM can learn to identify weapons based on their distinctive shape features.

FEATURE VECTOR GENERATION:

The selected observations are used to generate feature vectors for each image in the dataset. Feature vectors are numerical representations that encapsulate the salient characteristics of an image. For HOG observations, the feature vectors typically consist of gradient orientation histograms. The generation of feature vectors involves partitioning the image into smaller regions or cells and computing gradient histograms for each cell. These histograms are then concatenated to form a single feature vector that represents the entire image. The size and configuration of the cells can be adjusted to control the trade-off between feature granularity and computational efficiency. The feature vectors serve as the input to the HMM, enabling it to learn the relationships between these features and the presence of weapons. The choice of observation and the design of feature vectors are pivotal in the success of our weapon detection system. They allow the HMM to focus on relevant aspects of the image data and disregard irrelevant information.

TEMPORAL MODELING:

One of the distinguishing features of HMMs is their ability to model sequential data. In our project, this aspect is particularly significant since we are dealing with sequences of images. Each image in the sequence provides a piece of the puzzle, and the order of these pieces matters. HMMs are well-equipped to capture the temporal dependencies and dynamics in the data.

In the context of weapon detection, temporal modeling allows the HMM to learn the patterns and transitions associated with the presence or absence of weapons over a sequence of images. For example, the system can learn that weapons are more likely to appear after certain contextual cues or in specific spatial arrangements within the frame. To achieve effective temporal modeling, the HMM employs a set of hidden states that represent the underlying patterns or conditions in the image sequences. These hidden states evolve over time, reflecting the dynamics of weapon presence. The transitions between states are governed by transition probabilities, which are learned from the training data. By modeling these temporal dependencies, the HMM can make informed predictions about the presence of weapons at each point in the sequence.

HIDDEN STATE ESTIMATION:

A critical aspect of HMMs is the estimation of the hidden states from the observed data. In our weapon detection system, the hidden states correspond to the presence or absence of weapons. Given a sequence of images, the HMM's task is to estimate the most likely sequence of hidden states that best explains the observed data. This estimation is achieved through supervised learning. During the training phase, the HMM is provided with labeled data, where each image sequence is annotated with the ground truth information about weapon presence. The HMM learns the relationships between the observed features (in this case, the HOG-based feature vectors) and the hidden states (presence or absence of weapons). The training process involves parameter estimation, where the model learns the emission probabilities (the likelihood of observing specific features given a hidden state), transition probabilities (how the hidden states evolve over time), and initial state probabilities (the probability of starting in a particular state). Once the model is trained, it can be used to estimate hidden states in new, unlabeled image sequences.

MODEL EVALUATION:

A crucial step in the development of our weapon detection system is model evaluation. This step involves assessing the accuracy and performance of the HMM in identifying the presence of weapons. Evaluation is typically carried out on a separate test dataset that was not used during the training phase. The performance of the HMM is measured using standard metrics such as accuracy. This metrics provide insights into the model's ability to correctly detect weapons while minimizing false alarms. Achieving a balance between high accuracy and low false positives is essential for the practical utility of the system. The evaluation process also involves considering the model's robustness to variations in the data, such as changes in lighting conditions, backgrounds, and weapon types. A robust model should perform consistently across a range of real-world scenarios.

RESULT AND COMPARATIVE ANALYSIS: Hidden Markov Models achieved a test accuracy of 31.11%, suggesting challenges in effectively capturing temporal patterns associated with weapon presence in its current implementation. While HMMs are adept at handling sequential data, the complexity of the weapon detection task and the diversity in image sequences may hinder the model's ability to generalize well.

The lower accuracy could stem from HMMs' inherent limitations in capturing intricate temporal dependencies within image sequences. The dynamic nature of weapon detection scenarios, where the context of an image sequence significantly influences weapon identification, might pose difficulties for the model.

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Accuracy: 33.47%
Test Perplexity: -52073752.87023474
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The perplexity value of -156505608.7243697 for HMM presents a perplexing outcome. In the realm of Hidden Markov Models, perplexity serves as a gauge for how accurately the model predicts a sequence. The unexpected negative perplexity value suggests potential issues with the model's training or evaluation process. To unravel this peculiar result, a more in-depth investigation into the training procedure and parameter tuning is needed.

HOG, renowned for its strong feature extraction capabilities, demonstrated an impressive test accuracy of 83.33%. This outcome highlights the effectiveness of the HOG algorithm in accurately identifying weapons in images. The technique's proficiency in capturing gradient orientation distribution, regardless of color information, proved beneficial in scenarios with diverse lighting conditions and color variations.

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Final Test Accuracy: 83.33%
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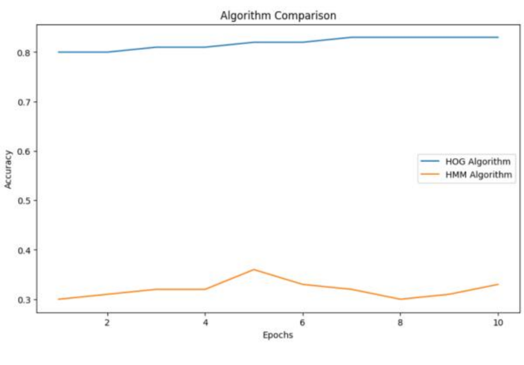
The elevated test accuracy suggests that HOG is particularly well-suited for our weapon detection task. Its success in detecting objects with distinct textures and shapes aligns seamlessly with the characteristics of weapons, establishing it as a reliable choice for this application. The model's ability to generalize to the test dataset underscores the adaptability and versatility of the HOG algorithm in real-world scenarios.



The significant contrast in test accuracy between HOG and HMM indicates that, when it comes to detecting weapons in images, HOG performs better in terms of accuracy. HOG's effectiveness lies in its capability to concentrate on distinctive features, offering a more efficient representation of weapons in images. On the flip side, the difficulties encountered by HMM in capturing pertinent temporal patterns underscore the complexities of applying sequential models to image data.

CONCLUSION: The study highlights the importance of selecting the right methodology for computer vision tasks. HOG excelled in weapon detection, while HMM faced challenges. This emphasizes the need to understand task characteristics for optimal methodology choice. The results guide further research in weapon detection systems, contributing to the discourse on machine learning in security. The negative perplexity for HMM calls for careful examination of its training and evaluation, presenting an opportunity for improvement.

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