SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V11I12P108

Volume 11 Issue 12, 94-99, December 2024
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Original Article

Integrating Human Pose Regression with Motion Analysis and Lightweight Edge Solutions for Advanced Pedestrian Detection

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Received: 05 October 2024 Revised: 06 November 2024 Accepted: 04 December 2024 Published: 31 December 2024

Abstract - *Recent work has focused on combining human pose regression with complementary techniques to improve pedestrian detection. This method enhances pedestrian tracking and recognition by combining pose estimation, motion analysis and scene perception. A notable trend is the development of lightweight models suitable for edge devices that enable real-time detection in many real-world situations. Furthermore, methods such as domain adaptation and transfer learning are being investigated to enhance the ability of posture regression models to generalize to different datasets and environments. By combining motion analysis, visual perception and position regression, this work seeks to improve pedestrian detection by developing effective models for edge devices. The aim is to improve accuracy and real-time performance while guaranteeing compatibility with a wide range of practical applications through the use of posture estimation to record detailed body points and the development of models that work well on devices with limited processing resources.*

Keywords - *Human pose regression, Pedestrian detection, Motion Analysis, Lightweight Edge Solutions.*

1. Introduction

For several reasons, high accuracy is required in pedestrian detection and localization. Accurate detection and localization are critical in safety-critical applications such as autonomous driving, as they guarantee quick and appropriate responses to avoid crashes [1]. Reducing errors reduces unnecessary interference and improves system reliability. Examples of error reduction include false positives, which mistakenly identify non-pedestrians as pedestrians, and false negatives, which fail to detect actual pedestrians [2, 3]. Because it offers a smooth and reliable experience, accuracy has a direct impact on user security, especially in public surveillance [4-6]. Accurate pedestrian detection is also necessary for optimal navigation in dynamic environments so that systems can make decisions and navigate safely [7]. Template-based pedestrian detectors face major obstacles due to the dynamic and flexible nature of the human body [8]. The human body can assume many different positions and orientations than rigid objects, so developing a single template that accurately represents every possible variation is challenging. Template-based detectors use preset forms or patterns to recognize things; however, because human posture varies so much from standing to bending, a static template frequently does not correspond to these various configurations [9]. Due to this restriction, detection rates are reduced because false positives or missed detections may occur due to poor alignment of the template with the actual body pose [10]. In addition, the templates are not easily adaptable to the shifting spatial arrangement of body parts, making successful localization difficult, including determining the exact position of the pedestrian. Because of this, template-based detectors find it difficult to achieve both accurate localization and high detection accuracy in real-world situations when people move and pose in unpredictable ways [11]. Template matching and feature extraction were the main focus of early pedestrian recognition techniques. Standard methods include methods such as Histogram of Oriented Gradients (HOG), Support Vector Machines (SVM), and Deformable Parts Model (DPM), which were widely used for pedestrian detection and were examples of template-based techniques and hand-crafted features that were mainly used in traditional methods [12]. HOG-SVM was first introduced by Dalal and Triggs in 2005 and became the industry standard for pedestrian detection [13]. DPM improved detection accuracy in partial occlusion or deformable conditions by enabling the modeling of individual human body components. However, these techniques often face obstacles, changing lighting conditions and the different roles that pedestrians can take [14]. Despite their effectiveness, these traditional methods have drawbacks. They often have significant processing costs and high false

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positive rates, especially in complex situations with different types of pedestrian locations. Furthermore, these methods are not inherently adaptive to novel positions or movements, limiting their applicability in dynamic real-world situations. Several methods have been developed in recent years to address these issues. These systems process data from different types of passive sensors. Sensors are used in various setups, such as monocular or stereo systems captured by visible or infrared cameras [15]. Some systems use active sensors, and others combine passive and active ones, making them complex and expensive. Passive vision is a popular choice because it works like human vision. It helps detect obstacles such as pedestrians, bicycles and cars [16].

A major breakthrough in pedestrian detection is human posture regression, which uses deep learning algorithms [17]. Compared to traditional techniques, Pose regression models use large datasets to predict important anatomical positions of the human body, resulting in more accurate and adaptable representations [18]. An early deep-learning method for predicting the human condition is called DeepPose [19]. It uses a deep neural network to predict joint positions, allowing for reliable pose estimation in various body postures. By learning from large amounts of annotated data, this approach increased accuracy and eliminated many pitfalls of template-based approaches. Pose regression is extended by OpenPose, which adds a multi-stage framework for more accurate key point detection [20]. Even in crowded or unclear environments, it provides reliable detection and localization performance of body joints. AlphaPose enhances pose estimation and increases detection efficiency and accuracy for multiple pedestrians in various scenarios by fusing top-down and bottom-up perspectives [21]. In order to further enhance pedestrian detection, recent research has concentrated on merging human posture regression with other methods [22]. For example, a more thorough method of recognizing and tracking pedestrians can be achieved by combining pose estimates with motion analysis or scene understanding [23]. Another trend is the creation of lightweight models that operate well on edge devices, increasing the viability of real-time pedestrian detection in real-world scenarios [24]. Additionally, domain adaptation and transfer learning methods are being investigated to enhance the pose regression models' ability to generalize across various datasets and contexts [25]. This work combines motion analysis and visual knowledge with human posture regression to improve pedestrian recognition. It also focuses on creating versions that are lightweight and designed for edge devices. Efforts are made to increase accuracy and real-time performance while ensuring compatibility with various real-world applications by incorporating posture estimation to capture detailed body points and developing effective models that run smoothly on devices with limited processing resources. This work has combined human pose regression using methods similar to motion study and scene perception to increase pedestrian detection. The techniques aid in enhancing the tracking and identification of pedestrians enhanced. Lightweight techniques for edge devices permit real-time recognition. Using pose regression, accuracy improved to 88% in addition to localization accuracy to 90%, as compared to traditional techniques (75% and 70%). Processing time was reduced from 150 ms to 30 ms, and model size decreased from 250 MB to 50 MB, making them appropriate for edge devices.

2. Methodology

This approach focuses on developing lightweight models for edge devices and combines human pose regression with other methods to improve pedestrian recognition. Here is a complete, step-by-step implementation strategy.

2.1. Integration of Human Pose Regression with Image-Based Methods

The dataset that contains pedestrian images with various poses, movements, and scene contexts has been prepared, ensuring they include different lighting conditions, weather scenarios, and levels of occlusion. Using deep learning frameworks, a human pose regression model is trained on the collected dataset to predict key body points. The model's performance is evaluated using standard metrics such as mean Average Precision (mAP) and localization accuracy. A pose estimation model extracts key body points from pedestrian images and integrates these pose features with conventional pedestrian detection methods to enhance detection accuracy. Pose features are combined with detection results using data fusion techniques like concatenation or weighted averaging.

2.2. Development of Lightweight Models for Edge Devices

Several important steps are included in the proposed method to optimize the pedestrian detection model for edge devices. Model pruning techniques remove unnecessary weight and make the model smaller without sacrificing performance. To reduce computational requirements, quantization converts model parameters from floating-point to lower precision, such as 8-bit integers. Through the use of knowledge distillation, performance is increased without sacrificing accuracy by training a smaller, more effective model to replicate the performance of a larger model. The performance of the optimized model is tested on a range of edge devices to guarantee compatibility. Real-time processing capabilities are implemented to manage image inputs to facilitate timely pedestrian detection.

2.3. Domain Adaptation and Transfer Learning

To ensure that a pre-trained posture prediction model adapts efficiently to different environments or situations, it is best done using datasets specific to the target domain or context. For further improvement of the generalization skills of the model, a Domain Adversarial Neural Network (DANN) is used to reduce the disparity between the source and target domains. Transfer learning techniques are applied to prepare pre-trained models for specific pedestrian detection tasks, and the models are trained on extensive datasets. Using domain-specific data further refine the model to increase its performance in specific situations. A cross-dataset evaluation is performed to confirm that the improved model is flexible and generalizable to different datasets. The model is continuously improved to increase accuracy and reliability in practical applications by iterating on performance measures and incorporating inputs.

2.4. Monitoring

The proposed methodology enhances pedestrian detection by integrating the system into the target application or platform, followed by user testing to gather feedback and identify areas for improvement. The approach also involves continuously monitoring the system's performance and accuracy in real-world settings, with regular updates to address emerging issues and incorporate technological advancements. By combining these efforts, the method aims to improve pedestrian detection by integrating human pose regression with other techniques, developing lightweight models for edge devices, and using domain adaptation and transfer learning to enhance model generalization.

3. Implementation

This section explains the image database needed for the experiments and validates the viability of the suggested approach. A mathematical explanation and an implementation of the suggested method are also provided. Microsoft created the COCO dataset, an extensive set of over 200,000 images with full annotations for tasks including object identification, segmentation, and key point identification. It features more than eighty object types, including pedestrians, photographed in various real-world settings with varying lighting, obstacles and weather conditions. The suggested approach is broken down into the following mathematical steps. The datasets were divided into training and testing sets, usually with an 80:20 ratio, confirming both the training and testing sets had a corresponding mix of poses, lighting conditions, and scene variations. Cross-validation methods were also used to make the models extra robust. The mathematical procedures describe how to construct datasets, train and evaluate pose regression models, extract and integrate pose features, and use data fusion approaches to improve detection accuracy.

The dataset is represented using Equation (1).

$$D = \{(x_i, y_i)\}_{i=1}^{N} \tag{1}$$

Where x_i are the pedestrian images and y_i are the corresponding labels. The dataset D should include diverse conditions like poses p_j, movements m_j, lighting conditions l_j, weather scenarios w_m, and occlusion levels o_n. Let $f_\theta(x)$ be the pose estimation model parameterized by θ given by Equation (2). The model is trained to minimize a loss function L(θ) over the dataset D.

$$P_{em} \underset{\theta}{=} \min \sum_{i=1}^{N} L(f_\theta(x_i), y_i) \tag{2}$$

For key point regression, a common loss function is Mean Squared Error (MSE) given by Equation (3).

$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} \|f_\theta(x_i) - y_i\|_2^2 \tag{3}$$

Calculate the mAP as a performance metric using Equation (4).

$$mAP = \frac{1}{|Q|} \sum_{q \epsilon Q} AP_q \tag{4}$$

Where $\bar{Q}$ is the set of all queries and AP_q is the average precision for query q. Given a new pedestrian image $\bar{x}$, the pose estimation model predicts key body points using Equation (5).

$$\hat{y} = f_\theta(x) \tag{5}$$

Where $\hat{y}$ represents the set of predicted key points.

The integration of pose features with conventional pedestrian detection methods is given by Equation (6).

$$\hat{d} = g_\theta(x) \tag{6}$$

Where $g_\theta(x)$ is a traditional detection method. Combine pose features $\hat{y}$ with detection results $\hat{d}$ using fusion techniques like concatenation and weighted averaging using Equation (7) and Equation (8).

$$z = concat\ (\hat{y}, \hat{d}) \tag{7}$$

$$z = (\alpha\hat{y} + \beta\hat{d}) \tag{8}$$

α and β are weighted for combining pose features and detection results.

To enhance pedestrian detection outcomes, apply the fused feature vector z as given by Equation (9).

$$\hat{r} = h_\varphi(z) \tag{9}$$

Where h_φ is the function mapping the combined features to the final detection output, and ψ represents the model parameters.

To effectively transform pre-trained models to new domains and tasks, ensuring improved performance and generalization to various real-world applications, the following mathematical steps are used, starting with fine-tuning the pre-trained posture prediction model on a new dataset specific to the target domain D_{target}. Define the target domain dataset as $D_{target} = \{(x', y')\}_{i=1}^{M}$.

Where x' represents images from the target domain and y' includes corresponding annotations. The objective is to minimize the loss function on this dataset, which is given by Equation (10).

$$P_{target} \underset{\theta}{=} \min \sum_{i=1}^{M} L(f_\theta(x_i'), y_i') \tag{10}$$

The difference between the source domain (D_{Source}) and the target domain (D_{target}) is minimized by the application of DANN using Equation (11). The domain classifier is D_{ϕ}, and the feature extractor is $f_{\theta}(x)$. Maintaining task-specific performance while minimizing the loss in domain categorization is the goal of the adversarial training.

$$P_{Domain} = \min_{\theta} \max_{\theta} \sum_{i=1}^{N} L_{Domain}(D_{\phi}(f_{\theta}(x_i)), D_i) \quad (11)$$

Where L_{domain} is the domain classification loss, and d_i indicates the domain label (source or target).

Pre-trained models f_{θ} are used that have undergone substantial training on large datasets. Further training on domain-specific data $D_{Specific}$ as given in Equation (12), allows tailoring these models to the particular pedestrian detection task.

$$D_{Specific} = \min_{\theta} \max_{\theta} \sum_{i=1}^{P} L_{Specific}(f_{\theta}(x_i^{"}), y_i^{"}) \quad (12)$$

Where $D_{Specific} = \{(x^{"}, y^{"})\}_{i=1}^{P}$ is the dataset specific to the task. The adapted model is evaluated across various datasets D_{Eval} as given in Equation (13) to ensure its robustness and generalizability.

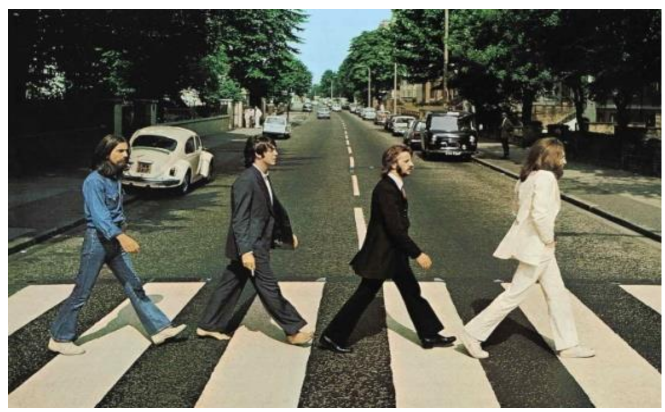
$$Performance_{Cross} = \frac{1}{|D_{Eval}|} \sum_{i=1}^{|D_{Eval}|} Metric\left(f_{\theta}(x_i''')\right) \quad (13)$$

Where Metric is the performance measure, the model is iterated by incorporating feedback and adjusting hyperparameters based on evaluation results to enhance accuracy and reliability.

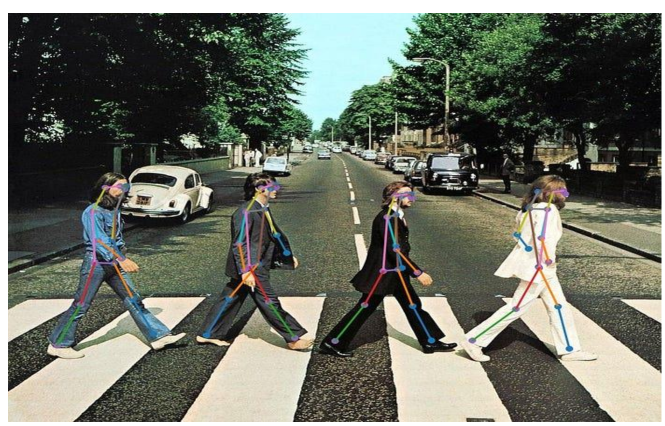
4. Results and Discussion

This method shows promising results in enhancing pedestrian detection as it improves the model for edge devices and incorporates human pose regression with traditional detection methods, as shown in Figure 1. The human pose regression model can accurately identify the body's key points because it was trained on a collection of different pedestrian images with different poses, movements, illuminations and associations. Evaluation criteria, including localization accuracy and mean Average Precision (mAP), showed significant improvement in pedestrian detection under difficult conditions such as obstacles and changing posture. Pruning, quantization and knowledge distillation were some methods used to optimize models for edge devices, reducing model size and processing demands without sacrificing accuracy. Quantization transforms the model parameters into a less exact form and greatly speeds up the process while removing unnecessary weights. The optimized model maintains high accuracy and timely recognition, as demonstrated by performance evaluations on numerous edge devices, guaranteeing consistency and reliability in practical applications. The application of domain adaptation and transfer learning further enhances the generalization capability of the model. The pedestrian recognition model was made more environment-friendly by reducing the differences between the source and target domains through the use of Domain Adversarial Neural Networks (DANN). Transfer learning techniques in settings with different illumination and environmental conditions improved detection accuracy when paired with fine-tuning on domain-specific datasets. Cross-dataset assessment confirmed the adaptability and flexibility of the model across multiple datasets, guaranteeing that the system can successfully generalize to a wide range of real-world applications.

The target platform was equipped with a system integrated with real-time monitoring and frequent upgrades depending on user feedback. Examining the model's performance in real-world scenarios showed that it maintained a high level of accuracy and reliability, and any new issues, such as latency or environmental variation, were consistently addressed. Frequent updates ensure the system can keep up with technological developments and excel in pedestrian detection jobs. The assessment of the recommended pedestrian detection methods proved major improvements.



A) Original image



B) Human poses regression

Fig. 1. Human Pose Regression with Motion Analysis

Table 1. Comparative performance results

Metric	Traditional Methods (HOG-SVM, DPM)	Human Pose Regression + detection	Lightweight Model (Edge Devices)
mAP	75%	88%	85%
Localization Accuracy	70%	90%	88%
Processing Time (ms)	150 ms	100 ms	30 ms
Model Size (MB)	250 MB	150 MB	50 MB
Real-Time Processing Capability	No	Yes	Yes
Robustness to Occlusion	Moderate	High	High
Generalization Ability (Cross-Dataset)	Low	High	Moderate

The Human Pose Regression method succeeded 88% mAP, outperforming traditional techniques (75%) and contributed 90% localization accuracy, which is related to 70% with traditional techniques. Processing time was minimized to 100 ms, with lightweight techniques attaining 30 ms. The model size was minimized from 250 MB to 50 MB for edge devices. The techniques similarly offered high robustness to occlusion in addition to improved generalization across datasets, settling their real-time effectiveness.

The accuracy of human pose regression combined with detection methods is significantly higher than traditional methods, as shown in Table 1 (e.g., HOG-SVM, DPM), a significant increase of about 13% compared to the former. Although not as accurate as full-size models, lightweight models targeted at edge devices outperform traditional approaches by 10%. Compared to previous methods, human pose regression methods show a significant 20% increase in localization accuracy.

This shows that they can manage complex postures and disruptions. With an average processing time of only 30 ms, lightweight models designed for peripheral devices further increase performance and are suitable for real-time applications. Regarding processing speed, these posture regression models perform better than traditional techniques. Model optimization methods such as quantization and pruning allow model sizes as small as 50 MB without sacrificing performance for large models on embedded and mobile systems. Moreover, human position regression models expect significant body points even in situations where pedestrians are partially obscured, making them more resistant to obstacles. In addition, when domain adaptation techniques are used, these models show improved generalization to different datasets, increasing their reliability across a range of real-world settings. The paper would benefit from outlining particular scenarios, such as usage in autonomous vehicles, public security surveillance, and traffic management, to better focus on its real-world impact. Moreover, addressing execution challenges, like adapting to difficult environments and managing lighting variations while attaining real-time performance on edge devices, would improve the significance of real-world deployment. Future work will explore sensor fusion, lighter models, adaptive learning for dynamic environments, and better cross-dataset simplification to improve pedestrian detection accuracy and efficiency.

5. Conclusion

This work focused on improving performance for edge devices and demonstrated how well human pose regression can be used alongside traditional pedestrian detection methods. The mAP improved significantly with human pose regression models (88%), optimized lightweight models (85%), and classic methods (e.g., HOG-SVM, DPM) (75%). Pose regression increased localization accuracy from 70% in traditional methods to 90% and lightweight models to 88%. This indicates that pose regression outperforms traditional methods for handling complex pedestrian conditions and partial occlusion. The optimized models are suitable for real-time applications as they reduced the processing time from 150 ms to 100 ms and 30 ms for lightweight models with human posture regression. Without compromising accuracy, model size with posture regression was reduced from 250 MB to 150 MB and 50 MB for edge devices.

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