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Generating photorealistic footprints

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Abstract
Crime scene footprints exhibit a high degree of variability due to a multitude of surface types (e.g., soil, carpet, and concrete) and lighting conditions. To efficiently study the use of deep learning techniques in footprint forensics, detailed datasets are needed. In this paper, we propose a novel approach to address the challenge of data scarcity. This approach uses anonymised real-world footprint data and high-resolution ground textures to create photorealistic crime scene images featuring footprints under various conditions. By leveraging GPU acceleration, our system streamlines this entire process, enabling the rapid generation of vast amounts of training data, complete with precise ground truth information.

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1. Introduction

Footprints are often more prevalent at crime scenes compared to fingerprints [1]. These imprints, found as residue or impressions on soft surfaces, hold valuable forensic evidence. Linking a specific shoe model to the crime scene is based on identifying variations between different models and molds of the same model [2].

Previous research explored footprint matching through encoded representations [3]. These encodings, created by forensic professionals, describe footprint features using the specific language of the matching tool. This language typically relies on descriptors such as shapes (stripes, circles), logos, text, and their frequency. However, locating a specific footprint in a database requires encoding it identically to the reference footprint, introducing subjectivity. As noted by practitioners, this variability can push the correct match further down the search results, significantly hindering the process.

Recent advancements propose mitigating human error in the classification of footprint patterns through computer vision algorithms. These algorithms automatically extract keypoints and descriptors from the footprint images. Examples include the Scale-Invariant Feature Transform (SIFT) [4] and Maximally Stable Extremal Regions (MSER) [5].

Although these computer vision techniques offer a significant improvement over manual encoding, they still rely on hand-crafted feature extraction. This dependence on predefined features can limit the accuracy of footprint matching, especially for complex patterns or degraded evidence. Emerging fields of deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image recognition tasks.

Despite the promise of deep learning for footprint pattern matching, significant hurdles remain in constructing the necessary datasets. Crime scene footprints exhibit a high degree of variability due to a multitude of surface types (e.g., soil, carpet, concrete) and lighting conditions. In addition, the sheer diversity of shoe designs and levels of wear further complicates data collection. Capturing this variability requires a large and diverse dataset that includes a wide array of surfaces, lighting scenarios, and shoe types. Obtaining such a comprehensive dataset ethically presents challenges, as images of real-world crime scenes often contain sensitive information. Addressing these data collection hurdles will be crucial in unlocking the full potential of deep learning for accurate and robust footprint pattern matching in forensic investigations.

Our proposed solution addresses the challenges of data collection in deep learning for footprint pattern matching by using automatically generated synthetic datasets. This approach uses anonymised real-world footprint data and high-resolution (4K) ground textures. Using computer graphics techniques, we can generate photorealistic synthetic crime scene images featuring footprints on various surfaces like soil, carpet, and concrete. This approach allows us to manipulate lighting conditions and introduce different shoe types with varying degrees of wear, all within a controlled environment. This enables the creation of a vast and diverse synthetic dataset that effectively mimics the real-world variability encountered at crime scenes. By overcoming the limitations of real-world data collection, our solution paves the way for training robust deep learning models for accurate and user-independent footprint pattern matching in forensic investigations. The high-level overview of the system can be seen in Figure 4.

2. Black and white footprints

The pivotal component in our process of generating synthetic data are the imprints of shoe outsoles. These imprints, readily available from existing forensic science datasets, serve as the foundation for the footprints we create within the synthetic scenes. Compiled by experts, these imprints typically represent the most recognisable tread patterns of various shoe models. They can be created through various methods, including ink impressions on paper, physical castings, or digital scans. Within our system, these black-and-white imprints are digitally "imposed" onto the high-resolution ground textures. The images of these footprints can be seen in Figures 1 and Figure 2.

3. Ground textures

Another cornerstone of our synthetic data generation is the utilisation of high-quality ground textures licensed under CC0 (Creative Commons Zero). This license ensures that the textures can be freely used for both non-commercial and commercial purposes. These textures have exceptional quality, reaching resolutions of 4K, which translates into incredibly detailed representation of real-world scenes. For enhanced realism, the textures often include additional layers beyond the base colour image. These layers, such as normal maps, roughness maps, and displacement maps, provide crucial information about the surface properties. The versatility of our system lies in its ability to take advantage of any texture that provides these comprehensive layers. This grants us access to a vast library of diverse ground textures, encompassing everything from soil and sand to carpets and concrete, allowing us to create synthetic crime scene environments that accurately reflect the real world. An example of the texture can be seen in Figure 3.

4. The 2D and 3D synthetic footprints

Our approach relies on the powerful capabilities of Blender, a free and open-source 3D creation suite. Using Blender's Python API, we can automate the process of generating synthetic crime scene imagery.

The final stage of our synthetic data generation pipeline revolves around the rendering of photorealistic footprint images. Here, the black and white shoe imprints are "imposed" onto the chosen ground textures. This integration takes into account the deformations present on the ground surface, such as cracks, stones, and bumps. This approach ensures that synthetic footprints realistically adapt to the underlying terrain, mimicking the way real footprints interact with the environment. The whole rendering pipeline can be seen in Figure 5.

Furthermore, alongside the generated image, a high-resolution ground-truth image is produced simultaneously. This ground-truth image acts as a reference, precisely labelling the location and details of the placed footprint within the scene. This process is sped up by using the GPU acceleration. These images along with the ground truth image can be seen in Figure 6.

5. Conclusions

We proposed a novel approach to address the challenge of data scarcity that hinders the application of deep learning in forensic tools for footprint detection and segmentation. Our solution tackles this problem by automatically generating synthetic datasets. This approach uses anonymised real-world footprint data and high-resolution ground textures to create photo-realistic crime scene images featuring footprints under various conditions. By leveraging GPU acceleration, our system streamlines the creation of vast amounts of training data, complete with high-resolution ground truth information. These photorealistic images hold immense potential for various computer vision tasks in forensics, including footprint detection, alignment, segmentation, and feature extraction.

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