MATERIAL-AWARE PERSON RE-IDENTIFICATION USING HYPERSPECTRAL IMAGING

Zhichao Zhang[*]*, Soon Heng Ang*[†]*, Jian Hong Tan*

Sensors and Sensemaking Centre Of Expertise
Home Team Science and Technology Agency
Singapore

Donovan Sim, Shahul Hameed Syed, Wen Sher Ong

Knovel Engineering Pte Ltd

ABSTRACT

Person Re-Identification (Re-ID) commonly relies on visible-spectrum appearance cues such as clothing color and texture. Consequently, individuals wearing visually similar garments remain difficult to distinguish using RGB imagery alone. This work investigates the use of hyperspectral measurements for material-aware Re-ID. We incorporate near-infrared spectral information to capture wavelength-dependent reflectance characteristics associated with fabric composition, providing complementary cues beyond visible appearance.

A visual–spectral fusion framework is developed to jointly encode RGB and hyperspectral information. To evaluate robustness to appearance ambiguity, we introduce a Counterfactual Material Swap (CMS) protocol that varies material spectra while preserving visible appearance. Experimental results demonstrate that hyperspectral information improves identity discrimination under challenging appearance conditions, highlighting the value of material reflectance signatures for person re-identification.

***Index Terms*—** Hyperspectral Imaging, Multispectral Fusion, Person Re-Identification

1. INTRODUCTION

Person Re-Identification (Re-ID) aims to associate observations of the same individual across multiple non-overlapping cameras. The availability of large-scale benchmarks such as Market-1501 [1] and DukeMTMC-reID [2, 3] has enabled significant advances in deep learning-based Re-ID systems. Nevertheless, existing approaches remain highly dependent on visible-spectrum appearance cues, making it difficult to distinguish individuals wearing visually similar clothing [4].

Recent studies have addressed challenges such as occlusion, viewpoint variation, and temporal appearance changes. However, these approaches continue to rely primarily on RGB imagery, where clothing color and texture may not uniquely characterize an individual. Garments fabricated from different materials can exhibit nearly identical visual appearance while possessing distinct spectral reflectance characteristics.

Near-infrared hyperspectral imaging provides access to wavelength-dependent reflectance information related to material composition. This motivates the investigation of material-aware Person Re-Identification, in which spectral measurements complement conventional visual features. In this work, we develop a visual–spectral fusion framework that jointly exploits visible-spectrum appearance and near-infrared hyperspectral information for identity recognition.

The main contributions of this work are as follows:

1. We introduce a material-aware Person Re-Identification framework that incorporates near-infrared hyperspectral measurements to capture fabric-specific spectral signatures.

2. We construct a multimodal VIS–NIR dataset spanning 400–1700 nm and propose a Counterfactual Material Swap (CMS) protocol for evaluating robustness to appearance ambiguity.

3. We study lightweight visual–spectral fusion strategies, including early fusion and cross-modal attention, and quantify the contribution of compact hyperspectral cues to identity discrimination.

2. RELATED WORK ON PERSON RE-IDENTIFICATION AND HYPERSPECTRAL FABRIC ANALYSIS

Cross-modal Person Re-Identification has primarily focused on matching visible and infrared imagery for low-light surveillance applications. Representative datasets include SYSU-MM01 [5], RegDB [6], LLCM [7], NTU-Corridor [8], and MP-ReID [9]. Existing methods largely address modality discrepancy through feature alignment and shared embedding learning.

Earlier work on hyperspectral Re-ID has also explored multi-camera spectral systems, including a pilot study by Prasad *et al.* [10], which demonstrated the feasibility of using hyperspectral cues for person identification across sensors.

Most infrared-based Re-ID studies instead rely on thermal imagery, where appearance is governed by emitted radiation

[*]Zhichao Zhang and Soon Heng Ang contributed equally to this work.

Table 1. Hyperspectral datasets for fabric analysis and spectral coverage.

Year	Dataset	Spectral Range
2017	SpecTex [18]	380 nm–800 nm
2018	HyTexiLa [19]	405.37 nm–995.83 nm
2024	DIH4AI OC2 [20]	900 nm–1700 nm
2025	NIR-SORT [21]	833 nm–2500 nm

and temperature distributions. In contrast, hyperspectral imaging measures wavelength-dependent reflectance tied to material composition. While RGB–thermal Re-ID has been extensively studied, hyperspectral material signatures for identity discrimination remain largely underexplored.

Hyperspectral imaging has been widely applied to textile characterization, material identification, and automated sorting [11, 12, 13, 14, 15, 16, 17]. These studies exploit fabric-specific spectral reflectance signatures to distinguish material composition.

However, existing work focuses primarily on fabric classification rather than person identification. Furthermore, available datasets generally cover only a subset of the visible and near-infrared spectrum. In this work, we investigate material-aware Person Re-Identification using measurements spanning 400 nm–1700 nm. A comparison of representative fabric datasets is provided in Table 1.

3. HYPERSPECTRAL DATA ACQUISITION AND PROCESSING

We acquire hyperspectral data using two Resonon imaging systems covering the visible and near-infrared spectrum (400–1000 nm and 900–1700 nm, respectively). Indoor acquisitions are performed using a controlled halogen illumination source, while outdoor captures rely on natural sunlight.

3.1. Imaging Setup and Calibration

For indoor data collection, a Resonon Benchtop Reflectance System is used. Both hyperspectral cameras are calibrated according to manufacturer-recommended procedures, including radiometric correction and dark current subtraction. All indoor acquisitions are recorded in reflectance units to ensure spectral consistency across sessions.

3.2. Outdoor Data Acquisition

Outdoor scenes are captured using a white reference tarp placed within the field of view to enable reflectance calibration under uncontrolled illumination. Targets are imaged at distances between 4 m and 10 m, with exposure settings adjusted to avoid sensor saturation.

Raw hyperspectral data are converted from radiance to reflectance using the corresponding reference spectrum derived from the calibration tarp.

3.3. Pose Dataset Acquisition

A controlled outdoor dataset of human subjects is also collected using the Pika L system. A single subject performs a set of representative poses (standing, walking, sitting) under varying viewpoints and distances. This ensures consistency in spectral characteristics while introducing geometric variation for analysis.

3.4. Spectral Band Selection

Hyperspectral measurements in the 900 nm–1700 nm range consist of 172 contiguous bands, many of which are redundant or affected by sensor noise. Following standard preprocessing, edge bands are removed and the water-vapor absorption region (1350–1450 nm) is excluded, resulting in 126 usable bands.

To evaluate compact spectral representations, we consider three band selection strategies: (i) a data-driven method based on IBRA–GSS [22], (ii) physics-guided selection using known near-infrared absorption regions, and (iii) uniformly spaced bands as a baseline approximation of low-cost multispectral sensing.

Physics-guided bands are selected around characteristic molecular absorption regions associated with textile composition, including C–H and O–H overtone regions in the near-infrared spectrum.

3.5. Fabric Categorization and Patch Extraction

Each hyperspectral sample is labeled into one of seven fabric categories (Cotton, Polyester, Nylon, Wool, Other Synthetics, Other Naturals, and Other Blends) based on dominant fiber composition (Table 2). The dataset is further divided into 4,051 image patches of size 20×20 pixels for band selection and classification experiments.

3.6. Band Selection Results

We evaluate selected band subsets (3, 6, and 9 bands) using the IBRA–GSS method, physics-guided selection, and uniform sampling. All subsets are evaluated using a consistent classification pipeline with stratified train/validation/test splits.

Table 3 summarizes the results. Overall, compact band subsets achieve performance comparable to full hyperspectral representations, with physics-guided 6-band selection achieving the best overall accuracy. Uniformly spaced bands perform competitively but are generally less discriminative than targeted selections.

Table 2. Fabric clustering rules and representative examples.

Cluster	Rule	Examples
Cotton	Cotton $\geq 70\%$	100% cotton; 80% cotton / 20% polyester
Polyester	Polyester $\geq 70\%$	90% polyester; 70% polyester / 30% wool
Nylon	Nylon $\geq 70\%$	100% nylon
Wool	Wool $\geq 70\%$	100% wool
Other Syn.	Synthetic (excl. polyester/nylon) $\geq$ 70%	PVC, polypropylene, spandex, acrylic, faux leather
Other Nat.	Natural fiber (excl. cotton/wool) $\geq$ 70%	Viscose, linen, hemp, rayon
Other Blends	No fiber $\geq 70\%$	50% cotton / 50% polyester; 60% wool / 40% acrylic

Table 3. Band Selection Methods for Fabric Classification (%).

Band Subset	OA (Mean $\pm$ SD)	F1 (Mean $\pm$ SD)
IBRA–GSS (3)	95.24 ± 1.12	93.71 ± 1.02
IBRA–GSS (6)	95.61 ± 1.08	94.57 ± 1.26
IBRA–GSS (9)	93.59 ± 1.94	92.53 ± 2.17
Physics (3)	93.12 ± 1.81	90.08 ± 2.60
Physics (6)	$\mathbf{95.93 \pm 0.97}$	$\mathbf{94.91 \pm 0.87}$
Evenly (6)	94.06 ± 3.62	92.74 ± 3.62

These results indicate that a small number of carefully selected wavelengths is sufficient to capture the dominant material-dependent spectral characteristics, motivating the compact VIS–NIR fusion design used in subsequent sections.

4. MATERIAL-AWARE PERSON RE-IDENTIFICATION

To investigate whether material information improves identity discrimination, we augment conventional visible-spectrum Re-ID with compact near-infrared spectral cues. Two fusion strategies are evaluated using a TransReID backbone.

For early fusion, six VIS–NIR channels are projected to three channels using a learnable 1×1 convolution:

$$y_c(x, y) = \sum_{i=1}^{6} w_{c,i} x_i(x, y). \quad (1)$$

We also evaluate a Cross-Modal Attention (CMA) module in which VIS tokens query NIR tokens and the resulting features are fused through a residual connection.

Table 4. Performance comparison of fusion methods (%). T and H denote the test and hold-out sets, respectively.

Method	T-mAP	T-R1	H-mAP	H-R1
VIS-only	19.1	13.2	23.0	16.7
1×1 Fusion	**92.9**	**94.0**	**95.1**	**96.7**
CMA	85.8	84.8	88.4	87.6

4.1. Counterfactual Material Swap Dataset

A synthetic VIS–NIR Re-ID dataset is generated by combining 60 human poses with paired VIS and NIR fabric textures. Clothing regions are assigned material-dependent VIS–NIR reflectance while skin, face, and background remain VIS-only.

To isolate material effects, visible appearance is held fixed while NIR material signatures are systematically permuted across six fabric categories. This produces the CMS-9216 dataset containing 9,216 synthetic identities, each represented by one query image and nine gallery images. Training, validation, and test identities are disjoint.

Table 4 shows that VIS-only Re-ID performs poorly under material permutations, achieving only 19.1% mAP and 13.2% Rank-1. Incorporating NIR information dramatically improves performance.

The 1×1 fusion model achieves the best results, reaching 92.9% mAP and 94.0% Rank-1 on the test set and 95.1% mAP and 96.7% Rank-1 on the hold-out set. CMA also substantially improves over VIS-only Re-ID but remains consistently below early fusion.

These results indicate that compact NIR material signatures provide strong discriminative information beyond visible appearance and can be effectively exploited using lightweight fusion mechanisms.

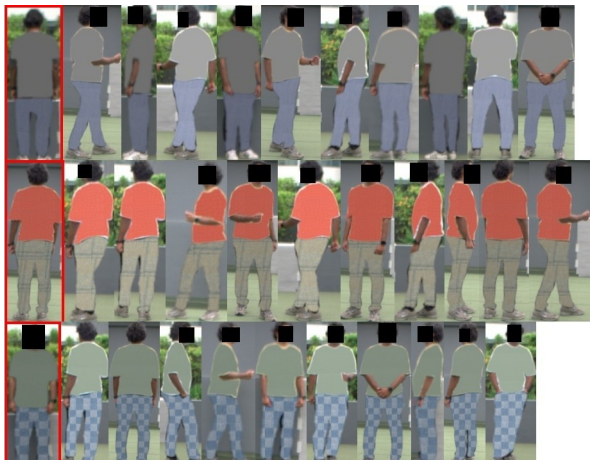


Fig. 1. Sample training data.

Table 5. Results of Black-Tee Stress Test

Method	mAP (%)	Rank-1 (%)
VIS-only (3-band)	71.4	60.0
1×1 fusion	63.1	60.0
CMA fusion	82.3	80.0

4.2. Case Study on 5 Black Shirts

To examine real world usage, we construct a stress test involving five identities wearing different black shirts. Similar to the setup used earlier, hyperspectral images of the same individual was taken, with VIS-only texture forming the base and only NIR information pertaining to the shirt region being copied over. The test data is here Fig 2 and results are provided in Table 5.



Fig. 2. Case Study on 5 Black Shirts

This experiment intentionally removes color and texture cues, forcing the model to rely on spectral information. Under these conditions, the VIS-only baseline achieves 71.4% mAP and 60% Rank-1 accuracy. Adding infrared information through simple early fusion does not improve performance, whereas the proposed cross-modal attention model significantly improves identification accuracy, achieving 82.3% mAP and 80% Rank-1 accuracy. These results demonstrate that infrared spectral signatures encode material properties that remain indistinguishable in visible imagery, providing a complementary signal for person re-identification under appearance ambiguity.

The relatively strong VIS-only performance is likely attributable to residual material diversity within the garment set. Although all shirts appear visually similar and are perceived as black garments, they were not explicitly selected to be material-homogeneous and likely comprise a mixture of fabric compositions, including cotton and polyester-based blends. As a result, subtle material-dependent reflectance differences remain present even within the visible spectrum and can still be partially exploited by the model.

Consequently, this evaluation should not be interpreted as a strictly material-constrained worst-case scenario. Since the model is trained to leverage material-dependent cues, its discriminative capability would be expected to increase when garments span a wider range of fabric compositions. The current experiment therefore represents a conservative validation case in which material diversity is limited despite the visually similar appearance of the garments. We expect the relative advantage of NIR-based fusion to become even more pronounced in larger and more diverse material settings, as well as under conventional RGB imaging where material-dependent reflectance information is less readily available.

4.3. Future Work

The results suggest that dense hyperspectral sampling is not strictly necessary for material-aware person re-identification, as most discriminative gains arise from a small subset of VIS–NIR bands. Future work will explore optimal band selection strategies, real multispectral Re-ID datasets, and physics-informed fusion models incorporating material reflectance priors.

5. CONCLUSION

This work investigates the role of hyperspectral sensing in person re-identification and introduces CMS, a counterfactual benchmark that isolates the effect of clothing material while controlling for visible appearance. Experimental results demonstrate that near-infrared spectral information provides complementary discriminative cues beyond RGB imagery. Simple VIS–NIR fusion yields substantial improvements on CMS, while cross-modal attention proves particularly effective in highly ambiguous same-color clothing scenarios. These findings highlight the potential of material-aware multispectral sensing for robust person re-identification under appearance ambiguity.

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