3D Scanning Technology for the Rapid Modelling of Fashion Clothing

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Abstract

The present research study addresses the prevalent issues of inefficient and time consuming garment pattern design in the fashion industry despite the recent advances in 3D product design. Fashion designers often lack efficient tools and readily available templates, which hinders their productivity and limits creative exploration. In order to overcome these obstacles, a solution that aids in garment pattern design by providing a comprehensive resource for content-based retrieval of image and 3D point-cloud data is proposed. The introduced software tool leverages a curated database to offer pattern designers access to an extensive collection of diverse garment designs, encompassing various styles, cuts, and aesthetics. The developed 3D point cloud retrieval architecture was designed to learn a similarity metric tailored for garments represented as 3D point clouds allowing the efficient exploration as well as selection of design patterns based on structural and stylistic attributes. Via the exploitation of machine learning algorithms, the retrieval architecture significantly reduces the time and effort required for the design ideation phase. Additionally, a demonstration of the applied process concerning the digitizing physical garments using a 3D structural scanner was seamlessly integrated utilizing real-world garments into the presented system and storing them in a digital pattern database. This approach represents a pioneering solution for rapid garment prototyping from the designer's standpoint, providing a valuable aid that accelerates the design process and encourages creative exploration. In addition, this research contributes to the literature on retrieval and metric learning for 3D garment fashion retrieval, opening that way new avenues for research and development in garment design, prototyping, and digital fashion innovation. In conclusion, the introduced software serves as a comprehensive solution that addresses the productivity hindrance faced by fashion designers, offering a transformative approach to garment pattern design and contributing to advancements in the field of digital fashion.

Keywords: 3d garment scanning, content-based retrieval, garment prototyping

1. Introduction

The emergence of 3D laser scanning technology has further revolutionized the fashion industry by enabling faster and more accurate data acquisition from object surfaces. By employing a 3D laser scanner, professionals can enhance the speed and precision of data recording. Consequently, this results in higher-quality data, which in turn improves visualization capabilities and overall productivity. The advancements in 3D scanning have also encouraged the utilization of cloud data capture, further expanding the possibilities of 3D modeling and animation. While the adoption of 3D scanners has been increasing across various industries, their use for building 3D models remains relatively limited in education compared to 3D modeling and animation software. However, integrating 3D scan data with 3D software and virtual technologies holds immense potential for design and manufacturing education. This integration enables designers to work with highly accurate data and construct complex organic shapes that were previously challenging to achieve using advanced 3D surface modeling software alone [1].
Amid environmental concerns, the fashion industry questions fast fashion's sustainability. 3D tech like visualization and prototyping aids in eco-friendly apparel manufacturing. Collaboration across the supply chain, longer clothing lifespan, and reduced impact are facilitated. Digital garment prototyping drives industrial change for sustainability. 3D virtual prototyping accelerates design with fabric and pattern experimentation on virtual models, yielding sustainable custom samples. These tools enhance speed, profitability, and align with green practices. Fewer physical prototypes lead to lower energy, transport, water, and chemical waste. Advantages include fewer samples, faster prototypes, higher quality, and informed decisions [2].

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Additionally, the rapid growth of digital media and its influence on fashion trends have compelled designers and fashion experts to incorporate new technological techniques [3]. This is necessary to meet current demands, improve productivity, and enhance the quality of customized clothing products. The impact of digital media is also evident in the field of 3D digital content production, such as movies, games, and advertising [4]. Designing and personalizing virtual characters with synthetic garments is a time-consuming process that aims to achieve satisfactory aesthetic results. To simplify this process, CAD (Computer Aided Design) software has been developed in recent years, but creating 3D clothing models still remains time-consuming and requires significant expertise.
One major drawback is that existing software does not align with the traditional design process, which involves starting with a 2D pattern, creating a physical prototype of the 3D garment, making adjustments based on imperfections, and repeating the process until the desired pattern is achieved.
The study proposes a new pipeline for rapid garment prototyping via 3D models. Designers start by loading a 3D model or scanning a physical garment. AI processes these models, extracting meaningful garment-specific features, which act as queries to a database. This database stores 3D garment files with their features and associated 2D patterns. The system offers curated 3D models and patterns for user selection, allowing modification for quick new garment creation. The paper follows a structured framework: Section 2 covers recent advancements in 3D scanning for fashion. Section 3 details data, preprocessing, and scanning. Section 4 presents a machine learning architecture for semantic extraction and retrieval. Section 5 showcases performance through detailed analysis. Section 6 concludes by summarizing findings and suggesting future research.

The paper presents the following contributions:

- Introduction of a novel dataset that comprises triplets of point clouds, images, and garment patterns, along with garment category annotations. This dataset provides a valuable resource for research in the field.
- Development of a robust 3D object recognition machine learning framework specifically designed for garment models represented as 3D point clouds. The framework initially undergoes pre-training in 3D point cloud classification and subsequently fine-tuning for various downstream tasks, including 3D garment model retrieval. This framework enables accurate and efficient analysis of garment models in a three-dimensional space.

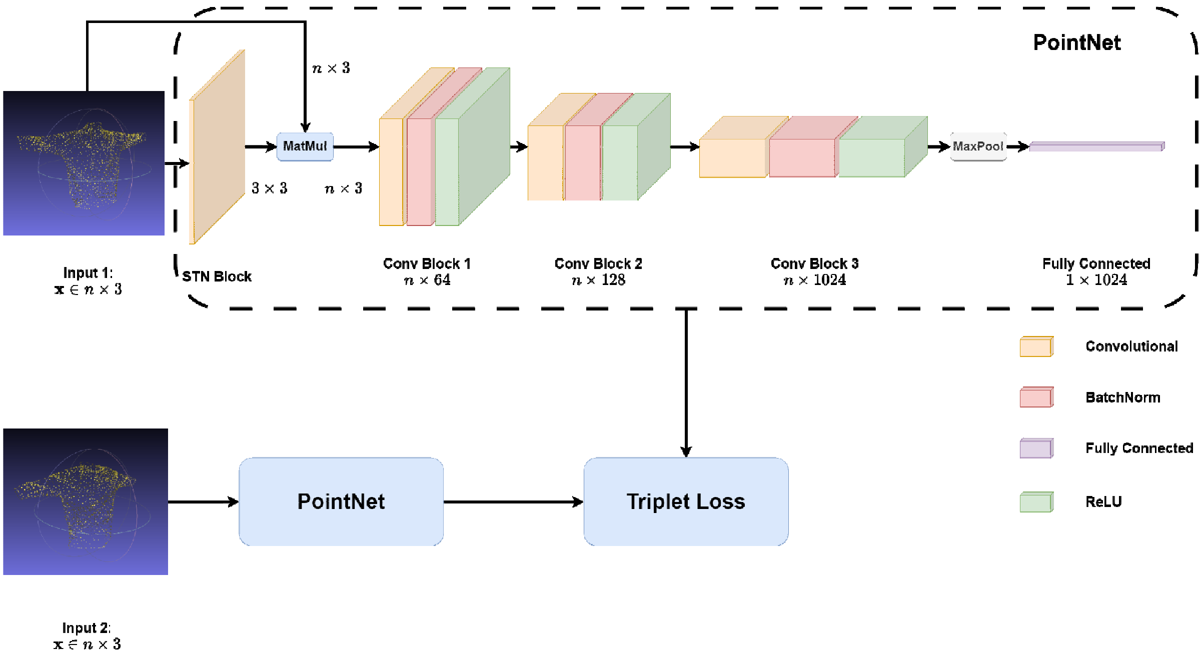

Figure 1 Our matching architecture. The architecture accepts two point-clouds as inputs. Inside the dashed lines we have the backbone architecture, PointNet [16] that is responsible for classifying and extracting semantic features from a 3D point cloud input. Both inputs are fed to the exact PointNet to extract a vector representation and then a triplet loss is computed in order to infer whether the two inputs match or not.

2. Related Work

As previously mentioned, contemporary computer-assisted techniques play a significant role in the realm of garment design, constituting a distinct industry. Numerous CAD design software solutions have emerged to streamline the modeling process. Noteworthy examples include Clo3D, vStitcher, and Optitex 3D [5, 6, 7]. These advanced 3D fashion design and development tools are specifically tailored for 2D pattern creation and 3D draping. They empower users to design garments encompassing size ranges, fabric variations, pattern adjustments, and achieve photo-realistic 3D representations. Nevertheless, the creation of 3D clothing models remains a time-intensive endeavor, necessitating substantial expertise on the part of the operator. Additionally, these programs are proprietary, lacking a standardized infrastructure for communication and exchange. However, the most prominent limitation lies in the software's inability to align with the conventional design process, which encompasses the journey from initial ideation to the ultimate realization of the garment. This traditional process entails designing in two dimensions, constructing physical prototypes of 3D garments, iteratively rectifying imperfections by reverting to the pattern, and repeating this cycle until the desired pattern is achieved [8].

The field of garment visualization and simulation had its early beginnings in the 1980s with Weil's pioneering work [9]. However, with the advancements in computer hardware performance, remarkable applications have emerged in this domain. Breen et al. (1994) [10] introduced a model that explicitly represents the microstructure of woven cloth using interacting particles. This model was utilized to predict the draping behavior of woven fabrics by incorporating measured data of real materials into energy equations for computer-based simulation. In a similar vein, Baraff et al. (1998) [11] developed a cloth simulation system that could handle large time steps without encountering numerical instability. They employed a triangular mesh to represent cloth surfaces in a physically-based manner. Keckeisen et al. (2004) [12] presented algorithms and techniques for simulating garment sewing, enabling interactive design and modification of garments within a 3D virtual environment. Volino et al. (2007) [13] proposed a technique that leveraged the natural motion of cloth towards equilibrium while minimizing the computation time required to determine the cloth's rest state by neglecting its velocity. More recently, Umetani et al. (2011) [14] introduced a system that facilitates interactive bidirectional editing between 2D patterns and corresponding 3D simulated forms. This approach allows simultaneous visualization of both 2D and 3D representations, enabling rapid prototyping and a better understanding of the draped form on a mannequin. The study addresses challenges related to geometric non-linearity and frictional contact during the simulation, employing various techniques such as isometric bending models, progressive refinement, and sensitivity analysis.

A follow-up work that attempts the unification of the garment design process is introduced in [15]. The authors propose a solution that accelerate this process by integrating deep learning techniques for retrieving garment models in the form of design patterns by providing the system with queries of the form of garment images or point clouds. Consequently, the user is catered with a set of tools that enables them to quickly edit, drape and export a new model.

3. Data Preprocessing

3.1. 2D and 3D Data

The aim of this section is to investigate the theoretical model of the proposed system, focusing on recording the specifications and the semantic characteristics of the digital pattern model. This model serves as the foundation for generating both 2D patterns and 3D garment models. The collection of garment patterns is stored in a database, forming the basis for creating 3D garment models.

To establish a digital database of pattern models, real garments need to be digitized. For this reason, pattern designs for three garment categories (blouses, skirts, dresses) were provided, which served as the basis for developing the digital pattern model. Specifically, data for 45 blouses, 35 skirts and 30 dresses along with their physical model were included in the database, serving as the foundation for the tools described in this paper. Figure 2 displays typical garments from the three studied categories in the project context. All identified key functional components of the subsystem are presented in Figure 3.

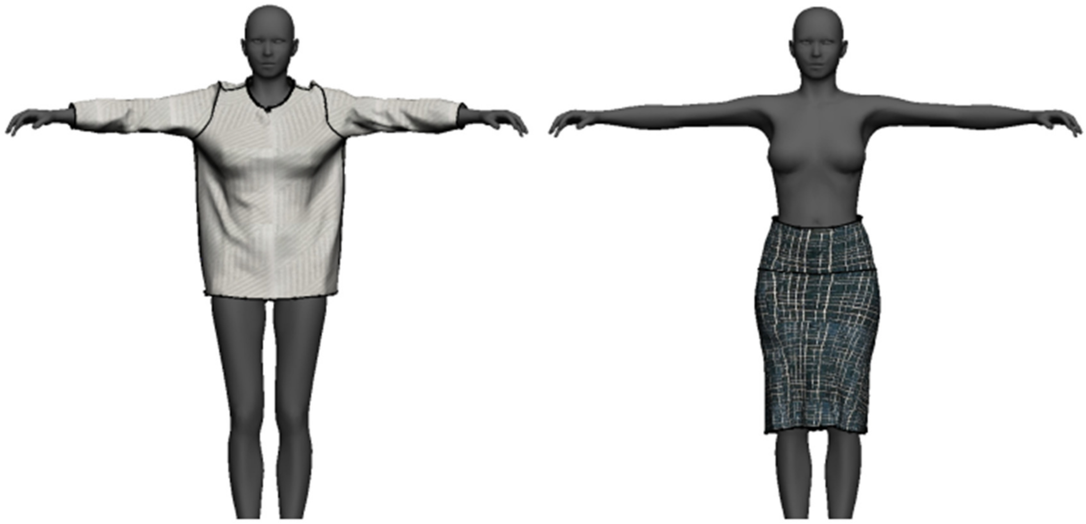

Figure 2: Three characteristic garments, one from each category

The initial stage involves collecting clothing patterns, which become part of the database for creating 3D clothing models. As mentioned above, the main clothing categories selected for the database are blouses, skirts and dresses, stored as digital pattern files in dxf format. The specific categories were selected through a discussion of the needs of the end users of the project and considering their usefulness to various customer categories. It should be noted that each clothing category adheres to specific pattern templates (see Figure 4). More specifically, a 'blouse' category garment comprises up to six different pattern categories (front body, back body, sleeve, cuff, collar, belt), as shown in the left part of the Figure below. Creating a pattern for each type of garment is essential to the development of the project's technology tools, as it provides software engineers with important information about the pattern's connectivity and restrictions. Similar rules apply to the other two clothing categories: 'skirt' and 'dress.'

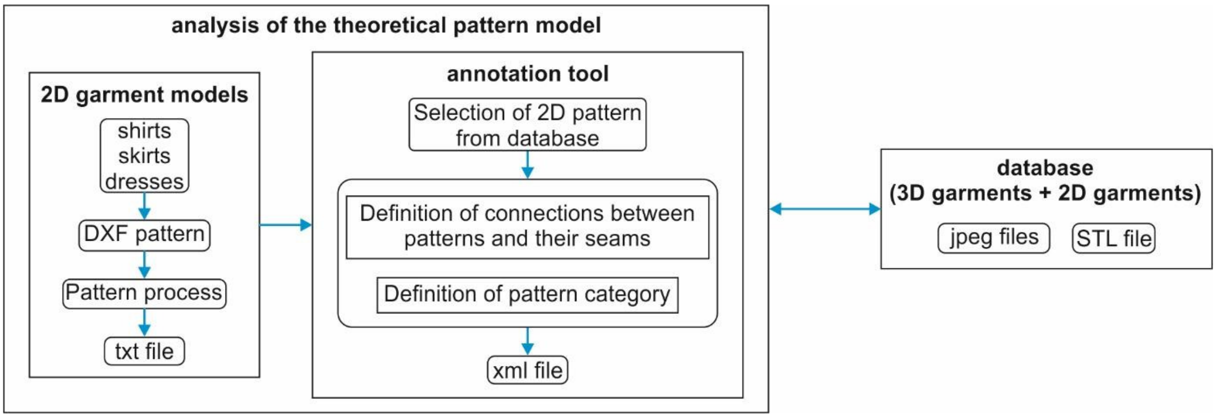

Figure 3: Architecture of the subsystem.

The pattern files in dxf format are then converted to svg format using a CAD software. These files with Scalable Vector Graphics (SVG) file extension use an XML-based text format to describe information about the patterns comprising the garment. In more detail, each file of this format contains the following information: The name of the garment (file), the name of the respective pattern and its individual parts. The new digital pattern files undergo processing using xml.dom.minidom and svg.path libraries, yielding plain text files with garment pattern points. Processed files then enter an annotation tool, enabling user-defined pattern specifications and semantic categories. Users can assign categories and connections (seams) to patterns using a database. Information is stored in .xml files, containing pattern details like name, category, geometry points, and seams. This database facilitates parameterization for dimension transformation and 3D simulation. Garments include xml, jpg, and 3D model files (obj or stl) for visualization. The library continuously adds new garments, forming a comprehensive pattern collection.

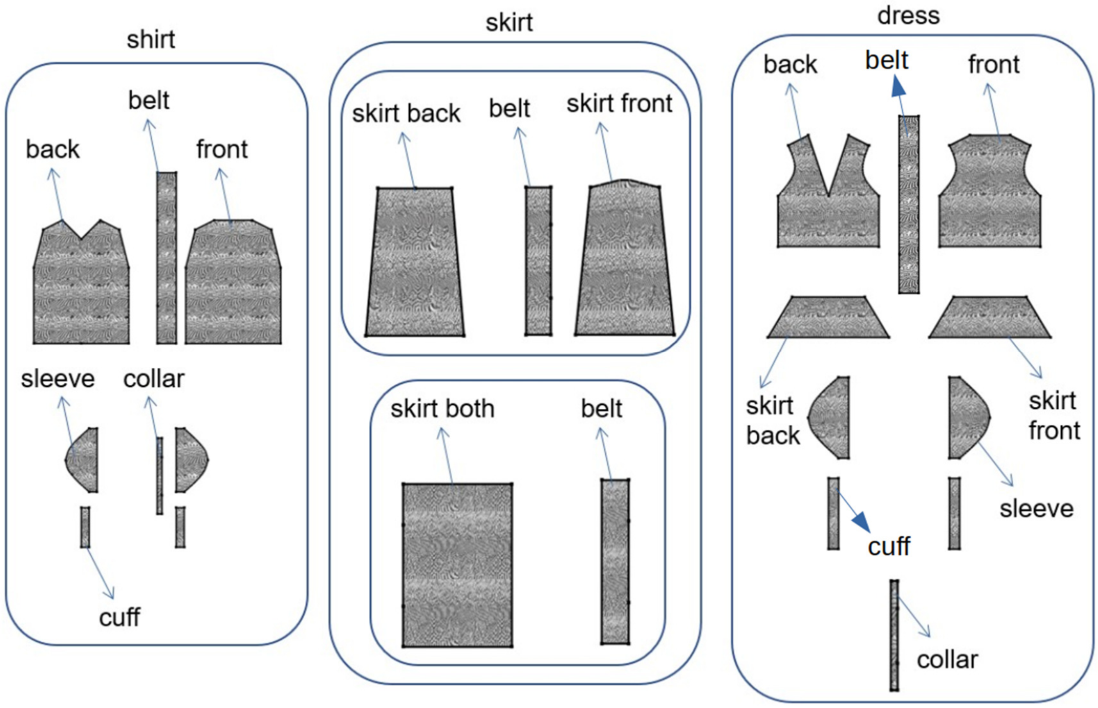

Figure 4: Clothing pattern template (shirt, skirt, dress).

3.2. 3D Scanning Process

The 3D scanning process for the blouse involves the following steps: First, the garment is placed on a stable human body dummy, ensuring even positioning and correcting lighting and fold points. Next, parameters and settings are defined for the 3D scan, including the number of images, object size, and scan resolution. The garment is then scanned using the handheld scanner Artec Eva™ 3D scanner, covering the entire surface from various angles. Artec Eva™ is a portable structured-light 3D scanner with an accuracy of up to 0.1mm for objects with the size of the garments. Moreover, the high-definition data acquisition was selected with up to 18 million points per second and a capturing speed was set at 16 frames per second to achieve maximum precision and accuracy. After scanning, individual downloads are previewed and evaluated for adequacy. These downloads are organized and merged, considering the chosen scanning strategy. The resulting 3D mesh is edited to address any discontinuities, holes, or imperfections using specialized software tools. The mesh is smoothed and prepared for conversion into a 3D garment construction design. It is worth mentioning that these post-processing steps were performed on the Artec Studio™ software. Finally, the 3D mesh is converted into a surface model and solid body, adding fabric thickness and verifying texture and color accuracy to produce the final 3D file of the blouse with comprehensive information.

4. Methodology

We present our model that is employed to retrieve designs of garment models from point clouds of scanned clothes. The fact that our inputs are point cloud data, the main hindrance we face is the lack of internal structure in terms of expressing a volume in infinitely many permutations, rendering the processing intractable. Therefore, we employ a permutation-invariant architecture in order to learn a representation in a n-dimensional space, where a point cloud of a scanned garment has unambiguous semantic meaning. That is, a point cloud is fed into a neural network, so that data points of the same class are close to one another and different classes are repelled. Our machine learning model is trained in two stages; the first one is fine-tuning a point cloud classifier and the second stage consists in minimizing a similarity cost in order to further discriminate the data points based on their classes, as well as based on their semantic content. In the following subsection we will be discussing the overview of the problem, as well as the challenges that need to be addressed. Afterwards, we will be briefly describing the proposed architecture that will accommodate the representation learning. Finally, we outline the training scheme adopted in order to learn similarities between point-cloud models within a latent space.

4.1. Preliminaries and Motivation

Given an input point cloud $\mathcal{P} \in \mathbb{R}^{N \times 3}$, where N is the number of vertices of the point cloud in the xyz space, our goal is to find a mapping $f: \mathbb{R}^{N\times 3} \rightarrow [0,1]^C$. Concretely, we seek to learn a parametric function f, that accepts a point cloud and predicts a vector of size C that represents the probability of participation for each of the C classes. The problem that emerges is twofold: First of all, by definition, neural networks are built so that they only accept fixed length inputs. Randomly sampling a fixed number of points from the entire pool of vertices, can mitigate the problem. Though, the problem of permutation-invariance still remains. Interchanging a small subset of indices in the set of the point cloud can lead a learnable function to produce undesired results [citation needed]. Nevertheless, it is computationally expensive.
The interaction among points within the point set is an important aspect to consider. These points exist in a space where a distance metric is defined, indicating that they are not isolated entities but rather part of a coherent whole. Consequently, it is crucial for the model to effectively capture the local structures present among neighboring points and understand the combinatorial interactions that arise from these local structures. Additionally, the learned representation of the point set should exhibit invariance under certain transformations. Given that the point cloud represents a geometric object, it is desirable for the learned representation to remain unchanged when subjected to specific transformations. For instance, rotating or translating the points as a whole should not alter the overall category of the point cloud or the segmentation of individual points. This property of invariance ensures that the learned representation remains consistent and robust regardless of the transformations applied to the input point set.

4.2. Architecture

The network architecture, as illustrated in Figure 1, describes the model's architecture as well as the learning strategy, for the similarity learning. The employed network comprises three key modules. Firstly, a max pooling layer is employed as a symmetric function to aggregate information from all the points in the input. This pooling operation ensures that the network can effectively capture relevant information from the entire point set. Secondly, the model incorporates a structure that combines both local and global information. This combination allows the network to leverage both fine-grained details from local regions and holistic information from the entire point cloud. By incorporating these two types of information, the network gains a comprehensive understanding of the input. Lastly, the model utilizes two joint alignment networks. The overall architecture is known as PointNet [16].

4.3. Learning

The approach to form an architecture for content-based retrieval is not straightforward and it is considered as a downstream task in computer vision problems. From a data perspective, it is required from the dataset to contain an adequate quantity of similar datapoints as well as a satisfactory number of diverse data points. From an architecture standpoint, for a model to be capable of performing retrieval tasks, they are trained primarily on classification tasks [17,18,19], as it commonly happens in content-based image retrieval tasks for fashion images. Similar to the case of images, we train the architecture proposed in [16] in two stages; the former involves training the model as a classifier on a fashion specific dataset containing point cloud data, which we will be describing in Section 5. Once the model is fine-tuned on the fashion specific dataset, the model minimizes a triplet loss cost function. Concretely, the representations computed from the activations of the layer before the classification module are fed to the triplet loss function:

$$\mathcal{L}_{tri} = \sum_{i=0}^{N} \left[\left\| f\left(\mathbf{x}_i^{anchor}\right) - f(\mathbf{x}_i^{+}) \right\|_2^2 - \left\| f\left(\mathbf{x}_i^{anchor}\right) - f(\mathbf{x}_i^{-}) \right\|_2^2 + \alpha \right]$$

In the function above, we have three vectors that correspond to the anchor, the positive and the negative samples in the batch of size N. The anchor is a data point drawn from the dataset of a class $c \in C$, while the positive is another data point of the same class as the anchor and the negative is a data point of different class than of the anchor. Therefore, the data points $\mathbf{x} \in \mathbb{R}^{H\times W}$ correspond to the image data, and the function $f(\cdot)$ is the result of the forward pass of the neural network that produces a latent vector $f(\mathbf{x}) \in \mathbb{R}^d$, which is a high dimensional vector representation of the point-cloud. When minimized, image representations with similar semantic content are expected to be projected closer in the latent space of $f(\mathbf{x})$.

5. Results

In this section, we will be discussing the details about the implementation, the datasets used, how the inference step is performed, as well as its overall performance. As the measure of performance of a content retrieval algorithm may be subjective, we will be presenting qualitative results in conjunction with the quantitative metrics.

5.1. Data

For the purposes of the fine tuning, we used the DeepFashion3D public dataset [21]. The dataset consists of annotated point cloud garment models, obtained from a scanning process. DeepFashion3D contains 2075 samples, comprised of 600 different models, where each model has in average 3 poses and is accompanied by one out of nine category labels. Curated mask labels are also included with the dataset annotations for point-cloud segmentation tasks, but segmentation is out of the scope of this work. The quality of data, combined with diversity renders this dataset an ideal candidate for a learning algorithm to be fined tuned on point-cloud fashion data.

5.2. Implementation

For both training and inference, the input point-cloud models undergo preprocessing to ensure they have a fixed number of vertices. Subsampling is accomplished through two methods: 1) random sampling, or 2) Poisson sampling. In our approach, we standardize the number of vertices for each model to be 2500. During implementation, we employ the Adam optimizer to perform parameter updates, employing a learning rate of 10^{-3} and $\beta = [0.9, 0.999]$. The training dataset comprises 80% of the data, while the remaining 20% is reserved for evaluating the model's progress. We train the model for 250 epochs with a batch size of 16. Our implementation concurrently optimizes both the classification cross entropy loss and the triplet loss. the input point-cloud models undergo preprocessing to ensure they have a fixed number of vertices. We also adopt an additional implementation where we standardize the number of vertices for each model to be 5000. During this implementation, we employ the Adam optimizer to perform parameter updates along with a step learning rate scheduler that decays the learning rate by 0.9 every 10 epochs. The training dataset comprises 80% of the data, while the remaining 20% is reserved for evaluating the model's progress. We train the model for 500 epochs with a batch size of 16.

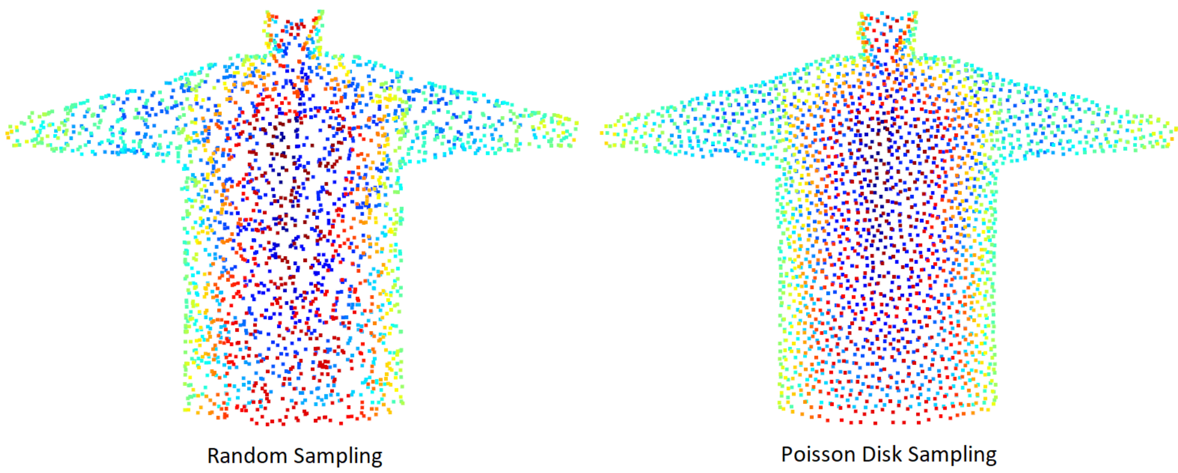

Figure 5 Visualization of the subsampled point-clouds with Random Sampling method (left), and Poisson Disk sampling method (right).

5.3. Inference

Once the model is trained, we move on to retrieving similar objects from scanned garments. This involves extracting deep feature representations from the penultimate layer of the trained model by inputting our available database as point-cloud data. For each entry in the database, we preserve the fixed-length vector representation of the point-cloud, along with the directory to the scanned model's file and its design information. When presented with an unseen query scanned point-cloud model from the user, the model processes the query and extracts its representation. This representation can be used to compute similarity scores between the query item and the items in the database. Several distance metrics are available to measure the distances between the query and candidate items for retrieval, including Euclidean distance, cosine similarity, and chamfer distance. In our experiments, we employ these aforementioned distance metrics. The models corresponding to the samples with the shortest distances are then returned to the user. The overall process is summarized in Figure 6.

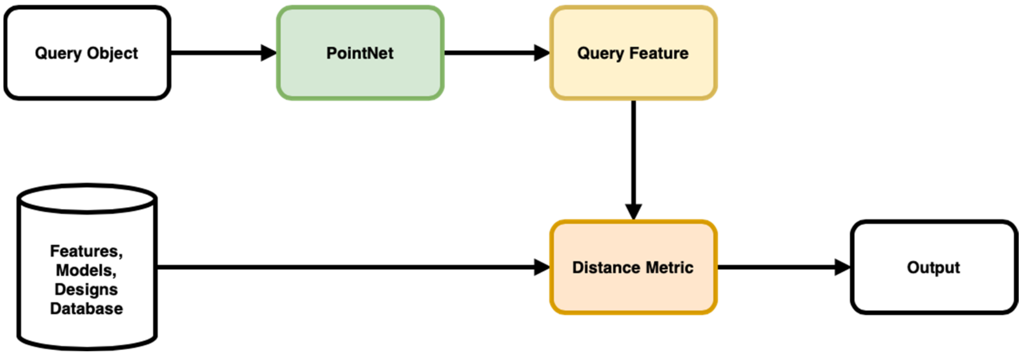

Figure 6 The procedure for retrieving similar garment models, along with their designs, begins with a user providing the system with a query point-cloud of a garment model. The system extracts the feature vector from the query point-cloud to create the Query Feature. Next, a distance metric is used to calculate the distance between the Query Feature and the feature vectors of the models in the database. The models whose features are closest to the Query Feature are then returned to the user as point-cloud models, accompanied by their respective designs.

5.4. Results

We thoroughly discuss the quantitative and qualitative results obtained from our proposed content-based retrieval system. The evaluation of our system employs the precision metric to assess the effectiveness of the results. We specifically chose the precision metric because it emphasizes the need for relevant items to be among the top elements in the retrieved collection of objects.
To initiate the evaluation scheme, we construct a database comprising pairs of point-cloud models and their respective feature descriptors. These feature descriptors are generated by feeding a portion of the original DeepFashion3D dataset into the fully-trained model proposed in Section 4 of our study. As the test set was not used for training the model, we consider it to serve as the "gallery set" that also functions as our database. Additionally, we randomly sample 40% of the training set to form the "query set".
To compute the performance of the retrieval architecture, the model receives a batch of queries along with their corresponding class labels. The model then computes the deep vector descriptors for these queries, and we calculate the distances between the query descriptors and those of the gallery set. For each sample in the batch, we sort the elements of the gallery set based on their distances, ensuring that the nearest gallery descriptor appears first. Subsequently, we compute the precision metric for each element of the batch, considering the class labels associated with the retrieved models.
We repeat this process for various values of K, which represents the desired number of retrieved elements to retain. Table 1 summarizes the performance of our retrieval architecture.

Table 1 Evaluation of the results on the test set on DeepFashion3D dataset. We used the precision at K, where K represents the number of items retrieved to measure the performance of our architecture. For the distance metric, we used the Euclidean distance.

# Of retrieved models	Precision (%)
@1	100
@2	87.4
@3	77.4
@4	55.0
@5	53.2
@6	52.4
@7	52.5
@8	43.0
@9	42.4
@10	40.6

5.5. Qualitative Results

To assess the qualitative performance of our method, we conducted experiments on three distinct categories: dresses, skirts, and blouses. In our evaluation, we used a query point-cloud model displayed in the left column and compared it against the remaining four columns, representing the retrieved garments. It is important to note that the model was not trained on this external dataset and was solely used for blind testing to evaluate the performance of our method. By employing this rigorous testing approach, we were able to objectively analyze the capabilities of our method and validate its effectiveness in retrieving relevant and visually appealing garments across different categories.

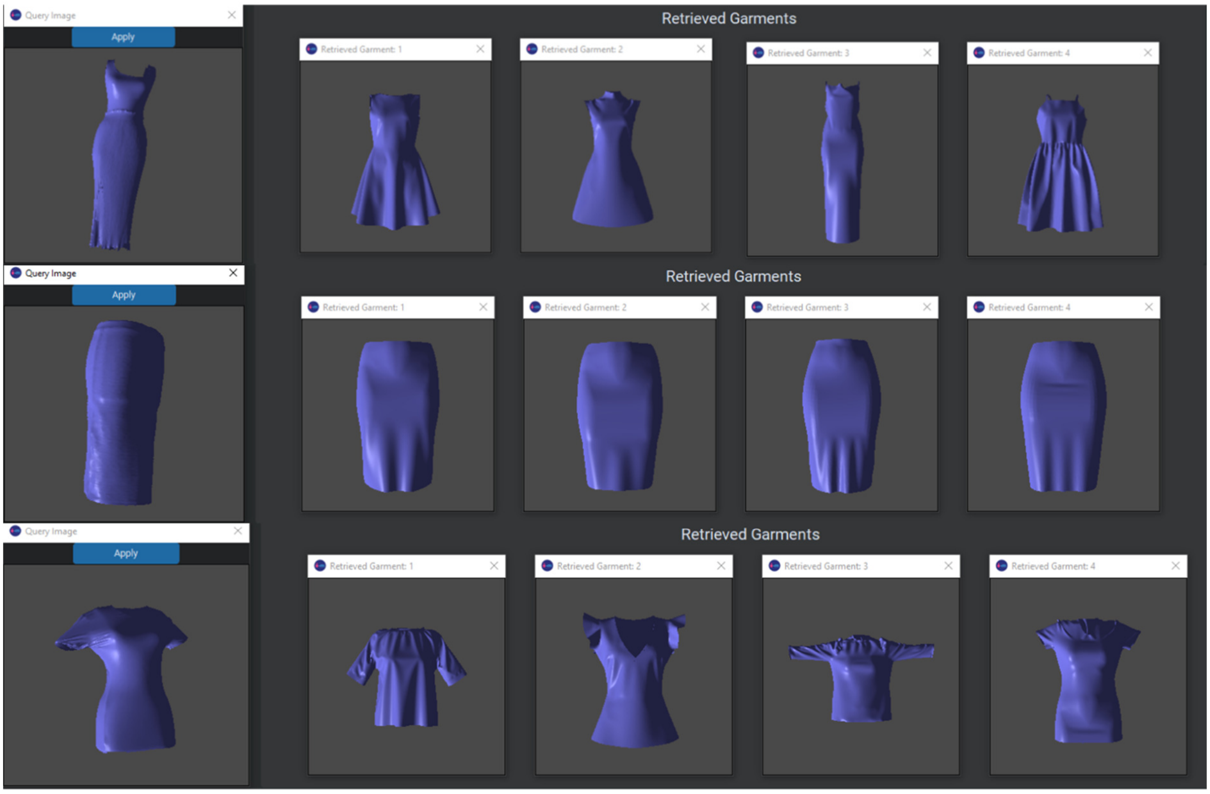

Figure 7 Results visualization of the retrieval architecture. The query point-cloud is on the left-most column. The query classes, from top to bottom correspond to: dress, skirt and blouse.

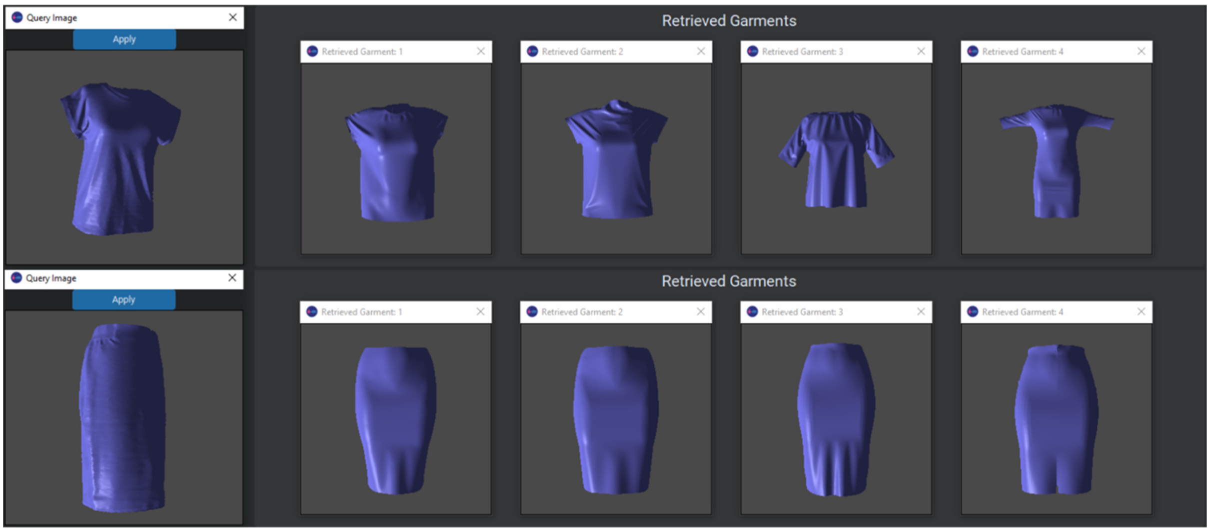

Figure 8 Results visualization of the retrieval architecture. The query point-cloud is on the left-most column. The query classes, from top to bottom correspond to: blouse and skirt.

6. Conclusion

In this study, we have introduced a straightforward and effective method for retrieving point-cloud models based on queries of the same type. Our work emphasizes the importance of data collection and pre-processing, which significantly impact the overall performance of the pipeline. Furthermore, we make a valuable contribution to the existing literature by introducing a novel dataset primarily designed for retrieval tasks. The evaluation results on a public dataset demonstrate promising outcomes, highlighting the model's aptitude for retrieval tasks and its potential in facilitating rapid garment prototyping. In addition to our achievements thus far, it is important to acknowledge that there is still much work to be done in this field. One crucial aspect that requires attention is the creation of high-quality annotations for our data. By providing detailed annotations, we can enhance the neural network's ability to recognize and differentiate between specific shapes and garment styles. Furthermore, it is essential to augment our dataset with a wider range of high-quality samples captured in diverse poses. This augmentation will contribute to the model's robustness and generalization capabilities, enabling it to perform effectively across various scenarios. These efforts will collectively advance the state of the art in garment prototyping and refine the capabilities of our model.

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References

[1] Kus, Abdil, Ertu Unver, and Andrew Taylor. "A comparative study of 3D scanning in engineering, product and transport design and fashion design education." *Computer Applications in Engineering Education* 17, no. 3 (2009): 263-271.

[2] Evridiki Papahristou & Nikolaos Bilalis (2017) Should the fashion industry confront the sustainability challenge with 3D prototyping technology, International Journal of Sustainable Engineering, 10:4-5, 207-214, DOI: 10.1080/19397038.2017.1348563

[3] Rocamora, Agnès. "Mediatization and digital media in the field of fashion." *Fashion Theory* 21, no. 5 (2017): 505-522.

[4] Särmäkari, Natalia. "Digital 3D fashion designers: Cases of atacac and The fabricant." *Fashion Theory* 27, no. 1 (2023): 85-114.

[5] CLO-3D, [Online], Available: https://www.clo3d.com/, Accessed 28 June 2022.

[6] VSTITCHER, [Online], Available: https://browzwear.com/products/v-stitcher/, Accessed 28 June 2023

[7] OPTITEX3D, [Online], Available: https://optitex.com, Accessed 28 June 2023

[8] Hulme, William H. The theory of garment-pattern making-a textbook for clothing designers, teachers of clothing technology, and senior students. Read Books Ltd, 2013.

[9] Weil, Jerry. "The synthesis of cloth objects." *ACM Siggraph Computer Graphics* 20, no. 4 (1986): 49-54.

[10] Breen, David E., Donald H. House, and Michael J. Wozny. "Predicting the drape of woven cloth using interacting particles." In *Proceedings of the 21st annual conference on Computer graphics and interactive techniques*, pp. 365-372. 1994.

[11] Baraff, David, and Andrew Witkin. "Large steps in cloth simulation." In *Proceedings of the 25th annual conference on Computer graphics and interactive techniques*, pp. 43-54. 1998.

[12] Keckeisen, Michael, Matthias Feurer, and Markus Wacker. "Tailor tools for interactive design of clothing in virtual environments." In *Proceedings of the ACM symposium on Virtual reality software and technology*, pp. 182-185. 2004.

[13] Volino, Pascal, and Nadia Magnenat-Thalmann. "Stop-and-go cloth draping." *The Visual Computer* 23 (2007): 669-677.

[14] Umetani, Nobuyuki, Danny M. Kaufman, Takeo Igarashi, and Eitan Grinspun. "Sensitive couture for interactive garment modeling and editing." *ACM Trans. Graph.* 30, no. 4 (2011): 90.

[15] Kaseris, Michail, Apostolos Boumpakis, Paschalis Charalampous, Ioannis Kostavelis, Sotiris Malassiotis, and Dimitrios Tzovaras. "i-Mannequin: A complete solution for Rapid Garment Prototyping." In *Proceedings of the 12th Hellenic Conference on Artificial Intelligence*, pp. 1-8. 2022.

[16] Jaderberg, Max, Karen Simonyan, and Andrew Zisserman. "Spatial transformer networks." *Advances in neural information processing systems* 28 (2015).

[17] Kuang, Zhanghui, Yiming Gao, Guanbin Li, Ping Luo, Yimin Chen, Liang Lin, and Wayne Zhang. "Fashion retrieval via graph reasoning networks on a similarity pyramid." In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 3066-3075. 2019.

[18] Hou, Yuxin, Eleonora Vig, Michael Donoser, and Loris Bazzani. "Learning attribute-driven disentangled representations for interactive fashion retrieval." In *Proceedings of the IEEE/CVF International conference on computer vision*, pp. 12147-12157. 2021.

[19] Kucer, Michal, and Naila Murray. "A detect-then-retrieve model for multi-domain fashion item retrieval." In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pp. 0-0. 2019.

[20] Kinli, Furkan, Baris Ozcan, and Furkan Kirac. "Fashion image retrieval with capsule networks." In *Proceedings of the IEEE/CVF international conference on computer vision workshops*, pp. 0-0. 2019.

[21] Zhu, Heming, Yu Cao, Hang Jin, Weikai Chen, Dong Du, Zhangye Wang, Shuguang Cui, and Xiaoguang Han. "Deep fashion3d: A dataset and benchmark for 3d garment reconstruction from single images." In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part I 16*, pp. 512-530. Springer International Publishing, 2020.