T^{2}GR^2: Textile Touch Gesture Recognition with Graph Representation of EMG

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***Abstract*—The fashion industry's negative impact and overconsumption require urgent action to improve and reduce fashion consumption. Tactile gesture plays a vital role in understanding, selecting, and feeling attached to clothes. In this paper, we introduce the FabricTouch II dataset with multimodal infromation, which focuses on fabric assessment touch gestures and aims to support sustainable fashion consumption. By integrating gesture labels, we enhance the dataset's comprehensiveness, improve recognition accuracy, and provide valuable information for consumers and intelligent systems, such as conversational agents in shop or home wardrobe. Additionally, this study has made preliminary explorations on recognizing fabric touch gestures using time-spectral representations of EMG combined with graph representations on this small batch dataset. The experiment found that the graph representation of EMG outperforms the regular neural network and that the representation capacity of bilateral EMG data is superior to that of unilateral data.**

***Index Terms*—textile touch, EMG, gesture recognition, GNN**

I. Introduction

The fashion industry is one of the most polluting industries in the world. It is responsible for a significant amount of greenhouse gas emissions, water pollution, and textile waste [1]. One of the main reasons for the fashion industry's environmental impact is overconsumption. People are buying more clothes than ever before, wearing them for a shorter time, and often throw clothes away after only a few wears if none [2].

To slow down and help our purchasing decision, it is critical that people engage in understanding the quality of the clothes material (so that it can last for longer) as well as understand our affective connection to it (e.g., pleasure, comfort, liking) [3]. Engaging with clothes involves tactile interactions that often get overlooked in our fast-paced fashion culture [4]. These tactile interactions are disregarded due to impulsive purchases driven by social pressures, minimal touching in stores to preserve the pristine condition of new clothes, or the abundance of clothes in our wardrobes [5]. However, At the same time touching is linked to more purchasing (REF Brain studies) and hence it is important to engage consumers in reflective tactile processes aimed to support both our decision process during shopping as well bonding once we buy the clothes. Simeng [6] has demonstrated the potential of conversational agents in facilitating individuals' tactile, reflective, and affective interactions with clothing materials. However, for conversational agents to be effective, it is crucial that they possess a certain level of awareness regarding how the consumers is touching the clothes to ensure that they trigger meaningful reflective prompts during their conversation. When we touch a material, tactile receptors in our skin are stimulated, and these signals are processed in our brain [7], leading to sensorial and affective judgments that help us classify materials and make subjective evaluations [8]. As such, different types of touch gestures and their kinematics are used to explore different properties of material [9] and different gestures are used by the expert in assessing the affective experiences that the material can provide (PETRECA 2013) [10] [11].

In this paper, we present the FabricTouch II dataset, with the aim to capture the fabric assessment gestures to support the long-term development of chatbot applications or conversational agents/robots that encourage reflective interactions with clothes material either while shopping in person or when browsing one's wardrobe. We leverage this dataset to investigate the automatic detection of fabric properties being explored by individuals and their subjective ratings based on touch behavior. The FabricTouch II dataset expands upon the previous FabricTouch Dataset [12], capturing hand muscle activity and arm movement data from 12 participants as they explore various garments using wearable EMG bracelets, alongside RGB images of each garment. This dataset is a multimodal collection that includes 16-channel EMG data from both human hands, three-dimensional accelerometer data, gyroscope data, magnetometer data, four-dimensional quaternion data, three-dimensional Euler Angle data, along with fabric property

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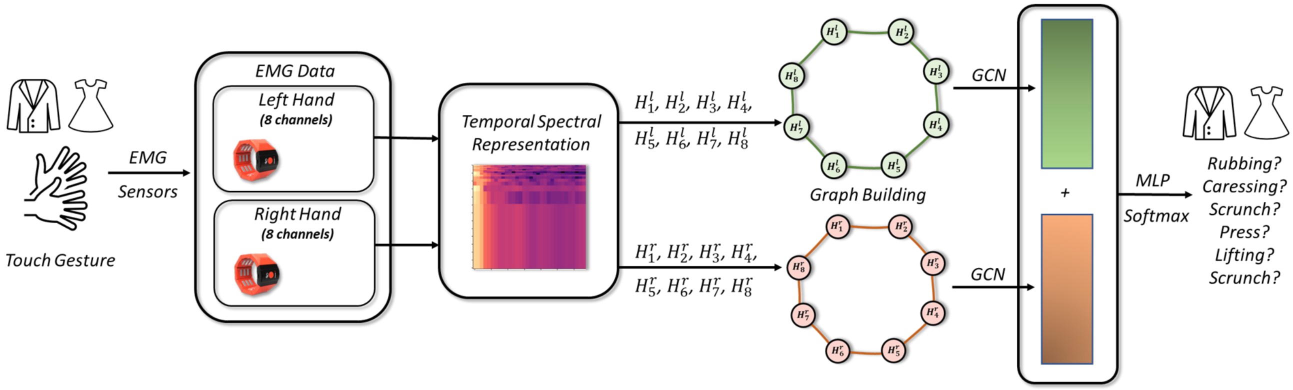

Fig. 1. **Our T^2GR^2 model pipeline.**

labels, fabric property rating, gesture action labels, and self-reported pleasure levels during fabric exploration. Building upon the previous FabricTouch Dataset, integrating predefined gesture labels and a novel algorithm enhances the dataset's comprehensiveness. This addition improves recognition accuracy for fabric properties and ratings, reveals relationships between gestures and identified properties, facilitates feature extraction for gesture variation analysis, and provides valuable information for consumers and intelligent systems, like chatbots, in textile interaction scenarios.

And this paper conducts a preliminary exploration with only EMG data in the dataset and builds up a graph neural network (GNN) model with the temporal-spectral representation of EMG. The pipeline of our Textile Touch Gesture Recognition with Graph Representation of EMG, namely T^2GR^2, as shown in Fig. 1. The both-hand EMG data are processed independently using Short-Time Fourier Transform (STFT) to obtain time-spectral representations. These representations are fed into separate two-layer GNNs to get individual global representations. Finally, the two global representations are combined for subsequent classification tasks.

In this paper, we conducted a comparison between normal neural networks (NN) and GNN models in the context of both single-handed and double-handed data inputs. The superior performance of our T^2GR^2 model, namely GNN with TSR features of dual-hand data, was confirmed.

II. Related works

A. Textile handling research

To facilitate effective communication of tactile experiences for informed product choices, various verbal descriptors have been explored to assess and communicate fabric properties [10] [13]. However, challenges arise when non-experts struggle to articulate their tactile perception, and cultural or individual differences in verbal expression hinder the construction of a systematic description of fabrics [4]. To bridge this communication gap, researchers have turned to kinematics and gestures as a means to convey tactile information. Studies have identified common gestures used by consumers to evaluate garments through touch, such as rubbing or stroking the edge of the garment [9]. Cary [14] further narrowed down the kinematic gestures to six common types used in textile assessment, including rubbing, pressing, stretching, lifting, scrunching, and caressing.

These gestures not only serve as a means of tactile evaluation but also enable the deduction of specific fabric properties being assessed [14]. For example, the speed of caressing has been found to affect the perceived level of softness [15]. This suggests the existence of a language of gestures in textile property assessment and opens up new possibilities for establishing a taxonomy of tactile language for textiles.

B. Automatic gesture recognition

The gesture recognition in textile interactions has the potential to capture and interpret kinematic data, allowing for the deduction of fabric properties associated with specific gestures. Past research has shown the existence of a language of touch that conveys sensory information and subjective experiences [9] [14]. However, further investigation is needed to establish the link between tactile patterns and individuals' experiences, with the support of gesture recognition technology.

When it comes to gesture recognition, two main approaches are used: vision-based recognition, which relies on analyzing video sequences captured by cameras, and wearable-sensor-based recognition, which utilizes devices EMG sensor [16]. Vision-based recognition faces challenges obstruction, spatial limitations, among others [17] [18] [19]. On the other hand, wearable-sensor-based approaches offer the potential for more natural interaction [17]. Recent studies have explored the application of wearable physiological sensors, particularly EMG, in capturing muscle activity during textile-handling activities for automatic gesture recognition and fabric property inference [20] [15] [21]. These studies have shown the feasibility of building automatic classification models to identify gestures and infer fabric properties based on subjective ratings. Wang's model achieved above-chance accuracy in classifying caressing, scratching, squeezing, and rubbing gestures [21]. Lin's study expanded on previous work by incorporating both arms and achieved accuracy above chance level for five fabric properties [15]. Despite some limitations, such as difficulties in recognizing gestures in real-world situations and sensor noise caused by arm deformation, using EMG-based armband sensors offers advantages in terms of user-friendliness, gesture recognition accuracy, adaptability, and cost-effectiveness [15].

III. METHODS

The objective of the research was to develop a machine learning algorithm for an automatic gesture recognition system based our new touch gesture dataset. This system is accurately categorize the gestures employed during textile evaluation, which can help infer the property being evaluated through the tactile interaction in the future research. This study sought to enhance the classification outcomes by encompassing possible gestural variations of commonly used gestures. Rather than relying on a predetermined (acted) gesture, this methodology facilitated a more comprehensive understanding and encompassed the extensive array of gestures encountered in real-life situations for better in-the-wild recognition results. In this study, our main emphasis lies on 5 key gesture and textile properties that have emerged from Cary's qualitative studies [14]. These gesture types and properties, namely rubbing - softness, caressing - smoothness, stretching - flexibility, pressing - thickness, and scrunching - softness. Additionally, we have included the gesture of lifting(- lightness), which was highlighted in a student report [15], to further enrich our analysis. Finally, the study also aimed to validate the correlation between a given property and the corresponding gesture proposed [14]. In this study, we collected a dataset and, as a trial study, built a GNN-based model with TSR features of EMG for tactile gesture recognition on our new dataset.

A. Participants

8 female participants were recruited, including 2 of whom had expertise in textiles. The participants' age range was 20 to 38, and all were right-handed. The study was approved by the Department Ethics Committee (NUMBER IF NOT BLIND).

B. Materials

1) Wearable Sensing Devices: For the experiment, two gForcePro+ electromyography (EMG) Armbands from OY-Motion were utilized. Each armband features 8-channel high-sensitivity EMG and 9-axis motion sensors, as well as Bluetooth BLE 4.2 connectivity and an elastic armband design. Two armbands were used to collect raw EMG and motion data from both arms. The armbands were worn on each arm, with the placement on one arm being a vertical flip of the placement on the other. A bespoke data collection app and Android phone - Moto g9 power, running on AndroidTM 10 with a Qualcomm® SnapdragonTM 662 Mobile Processor and Bluetooth 5.0, were used for the experiment. In our dataset, we collected the EMG and motion data while for the trial exploration with AI models, we only used EMG data.

2) Clothes: Six garments were selected by the researcher for inclusion in the experiment. The selection aimed to ensure representation of various fabric properties across different garment types and material types, capturing the real-life variability of clothing handling gestures. The garments included puffed jackets, synthetic sweaters, silk skirts, jeans, wool-based sweaters, and cotton shirts.

C. Data collection protocol

The data collection was conducted in a laboratory environment using the six clothes and six gesture types (rubbing, caressing, stretching, pressing, scrunching, and lifting) [9]. The order of the fabrics was counterbalanced to reduce order effects. After placing the armbands on participants' arms and gathering a signal baseline to ensure the setup was working. Participants were set in a simulated shop setting and aimed to collect free exploration gestures. Participants had a 20-second interval to explore each garment, as previous studies have found this duration to be adequate [20] [15]. They were then asked to rate each fabric preference separately on a Likert scale ranging from 1 to 7. Both the EMG data and the ratings were collected for future machine learning study applications.

In the second phase, participants were given a specific fabric property to evaluate and asked to evaluate the property by using specific gestures. These properties and gesture types were based on previous study [14] [9](rubbing - softness, caressing - smoothness, stretching - flexibility, pressing - thickness, scrunching - softness, and lifting - lightness). Participants were allowed to interpret the gesture types in their own way, and the researchers provided various demonstration examples if people did not understand the name of the gesture. After exploring a given gesture and property for a particular garment, participants rated the garment on the corresponding property scale (e.g., from 'rough' to 'smooth' for the smoothness property). They also selected and repeated their favorite gesture with the fabric and provided a rating on a 7-item Likert scale ranging from 'not at all' to 'very much'.

D. Data processsing and model

Due to the intermittent Bluetooth connectivity issues during the data collection, we retained only samples containing simultaneous wristband readings on both hands. During experiments, the EMG data was recorded with a sampling rate of 500 Hz and 12 bit of each frame. Given the high sampling rate, our software system captured and stored data every 16 frames, defining this as a basic data unit. We extracted peak values, averages, and Root Mean Square (RMS) values for each unit. Ultimately, we selected to use the RMS value as the distinguishing feature for each basic data unit. RMS is chosen as a key feature in EMG analysis because of its ability to reliably estimate signal amplitude - a characteristic closely associated with muscle activity, along with its smoothness and stability over time, and its inherent non-negativity. Furthermore, to simplify the data preprocessing, we standardized all sample lengths to a uniform 600, guided by the probabilistic distribution of sample size and based on the truncation operation and zero-padding operation.

And then we also carried out a variety of preprocessing on the EMG data, including the Butterworth bandpass filter

TABLE I
ACCURACY OF MODELS

Acc	Left hand	Right hand	Both Hnads
NN	0.24	0.28	0.32
GNN	0.28	0.32	0.36

configured with a lower cutoff frequency of 10 Hz and an upper boundary of 240 Hz, the moving average operation to smoothen the data, the utilization of a full-wave rectifier to convert all signal values to positive, and the Z-Score Normalization for standardizing the data.

For feature extraction, we used STFT upon preprocessing. It uses the Hanning window function, a window size of 50, and a step of 25, a Fast Fourier Transform (FFT) size of 100. STFT offers a dual-dimensional representation encompassing both time and frequency domains, thus maintaining the specifics of frequency information localized in time. It proves advantageous when handling non-stationary signals (EMG et al.).

For our T^2GR^2 model, EMG data of both hands are subjected to the STFT to obtain temporal-spectral representation (TSR) of each channel over time. The global information of the left and right-hand EMG is acquired through graph-based representation. As both the left and right-hand rings have eight channels each, the construction of the graph structure is based on the principle of adjacency, forming an undirected cyclic graph. The node features of the graph are TSR features of the entire EMG series of each channel. Finally, the global graph representations of the left and right hands are fused to achieve the task of touch gesture classification. The dataset is randomly divided for training with 128 samples, validation with 20 samples, testing with 25 samples. For our T^2GR^2 model training, we used the Adam optimizer with a learning rate of 0.005 and the dropout layer with a dropping rate 0.5.

IV. Results

In addition to our T^2GR^2 model, we also compared the GNNs model with left-hand and right-hand data, respectively, and regular NN models with left-hand data, right-hand data, and both-hand data, respectively. As shown in Tabel I, the GNN model performed better than the NN model in all our tests. The reason is that the GNN model was better able to learn the structural features between the EMG channels, enabling a higher capacity in gesture recognition. The regular NN model may encounter difficulties handling this type of structural information. The results showed that the both-hand model outperformed the single-hand model in gesture recognition on both the NN and GNN models. It is because both hands' data contained a more comprehensive range of information for understanding and recognizing gestures.

V. Discussion and Future Work

While the model's recognition rate is inherently limited, this is deemed acceptable given the modest scale of the dataset and the substantial challenges involved in touch gesture recognition only with EMG. The low recognition accuracy is attributed to various factors. Mainly, each gesture embodies various patterns, presenting a challenge to the model. The future work will focus on big dataset building and multimodal touch gesture recognition with EMG and motion data.

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