SPD Siamese Neural Network for Skeleton-based Hand Gesture Recognition

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Abstract: This article proposes a new learning method for hand gesture recognition from 3D hand skeleton sequences. We introduce a new deep learning method based on a Siamese network of Symmetric Positive Definite (SPD) matrices. We also propose to use the Contrastive Loss to improve the discriminative power of the network. Experimental results are conducted on the challenging Dynamic Hand Gesture (DHG) dataset. We compared our method to other published approaches on this dataset and we obtained the highest performances with up to 95,60% classification accuracy on 14 gestures and 94.05% on 28 gestures.

1 INTRODUCTION

Hand gesture recognition is an important topic that can be used in many fields such as sign language recognition, robot control, virtual game control, human computer interaction, etc. Consequently, improvement in hand gesture interpretation is becoming an active research area for the past 20 years. The development of recent sensors such as Microsoft Kinect or Intel Real Sense brought great opportunities for this domain. In fact, many approaches have emerged using hand skeletal data that can be acquired with good precision using these sensors. Among the various proposed approaches to represent and recognize hand sequences, SPD networks showed most reliable methods using skeleton representations and deep neural network approaches using manifold based-learning. Besides, they provide powerful statistical representations for the skeletal data. Several researches were conducted in this field, and new networks were proposed, such as the SPD network proposed by (Huang and Van Gool, 2017) and in turn was developed by (Nguyen et al., 2019) in order to improve the performances. Motivated by this observation, we have decided to continue improving these proposed models. For this, we have decided to integrate an SPD network in a Siamese network for several reasons among those we cite the great success of the adoption of the Siamese network in many computer vision and machine learning applications such as; face recognition, handwriting recognition, and visual tracking. One more advantage of the Siamese networks is their ability to handle the issue of the lack of training data. On the other hand, the SPD representation has been employed in many areas including shape retrieval (Tabia et al., 2014), medical imaging (Jayasumana et al., 2013), and pedestrian detection and tracking (Tuzel et al., 2008). Recently a Riemannian network for SPD matrix learning has been introduced by (Huang and Van Gool, 2017). The proposed network opens new directions to explore, in particular the application of the deep learning on Riemannian representations with SPD matrices. In this article, we explore the usage of Siamese networks on SPD matrices for hand gesture recognition.

A positive symmetric matrix network is adopted as a starting point for the Siamese network. To the best of our knowledge, this is the first approach that combines a positive symmetric matrix network with a Siamese network. This paper has two main contributions:

- It focuses on symmetric positive matrix networks and it develops candidate networks to get the best accuracy.
- It combines the properties of this network with the Siamese approximate properties of similarity in order to improve the efficiency of our network

The rest of this paper is structured as follows. In section 2, related work on hand gesture recognition and deep learning manifold-based approaches are reviewed. In Section 3, our proposed approach is de-

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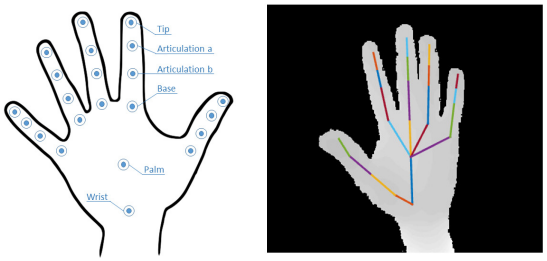
scribed. In section 4, experimental evaluations are reported. Finally, the last section is dedicated for the conclusion.

2 RELATED WORKS

In order to examine the subject of hand gesture recognition particularly and action recognition generally, several approaches have been devised to mainly two groups in order to obtain better architecture. In one hand, there are traditional methods based on position detection, dense trajectories such as method based on video modeling by combining dense sampling with feature tracking and calculating boundary features along dense trajectories (Chen et al., 2015). On the other hand, several new vision-based methods and new deep learning networks have been invoked, such as: recognition via sparse spatio-temporal features based on CNN and LSTM using RGB sequences (Sukthanker et al., 2020), convolutional Two-Stream Network Fusion for video action recognition (Feichtenhofer et al., 2016) Deep 3D CNN (Wang et al., 2016), reduction of hierarchical characteristics and deep learning (HFR-DL) proposed by (Sukthanker et al., 2020)

In addition, there are many methods proceeding skeletal data captured by the depth sensing cameras. As illustrated Figure 1, this skeletal data is composed of a set of 3D joints. They deal generally with non-Euclidean spaces such as elastic functional coding of Riemannian trajectories (Anirudh et al., 2016). Some approaches focus on Lie groups methods such as the deep learning neural network on Lie groups for skeleton-based action recognition proposed by (Huang et al., 2017) and based on the succession of the proposed RotMap + RotPooling block. The RotMap layer transforms the input rotation matrices and the RotPooling and the RotPooling layer pools the resulting rotation matrices temporally and spatially. The proposed network is finalized by a LogMap Layer. In the same field, Vemulapalli et al. proposed in (Vemulapalli and Chellapa, 2016) a neural network. It starts with a Skeletal representation using 3D rotations between the body joints. Then comes the warping layer to compute the nominal curves and warp all the curves to it. Along these nominal curves, a RollingMap layer are applied on the Lie group over its lie algebra and the actions are unwrapped onto this lie algebra. These unwrapped actions are finally transformed into feature vectors and are classified using the linear SVM classifier. Others studies focus on Grassmann manifolds and proposed new Grassmann network architecture (Huang et al., 2018) composed of 3 major blocks: Projection block, Pooling block and output block. The Projection block is intended for the transformation of the orthonormal input matrices. The Pooling block is designed to map the orthonormal matrices and apply a mean pooling on them. These outputs are vectorized and classified in the output block. However, the major problem with many of these methods is that they sometimes distort the nature of the data or lose some information related to the basic characteristics of the input data. To deal with this problem, many studies oriented to the SPD matrices which are characterized by its advantage in preserving the basic characteristics of the data. Thanks to their ability to learn appropriate statistical representations while respecting Riemannian geometry of underlying SPD manifolds, SPD matrices have been popular in computer visions researches. Many studies carried out on SPD matrices have managed to create new approaches and methods exploiting SPD matrices characteristics. Among these approaches, we mention the Riemannian network proposed in (Huang and Van Gool, 2017), Riemannian Metric Learning for Symmetric Positive Definite Matrices (Vemulapalli and Jacobs, 2015) (Lim et al., 2019) which used SPD manifold geodesic and exploited SPD matrix distances properties to the images clustering, face matching problems. (Sukthanker et al., 2020) proposed a neural architecture research which grouped many SPD networks layers and different SPD methods and choose the optimal SPD network path.



(a) (b)

Figure 1: Skeletal hand joints.(a) Hand joints illustration. (b) The full skeleton returned by the Intel Real Sense.

3 THE PROPOSED APPROACH

In this section, we present our network model referred to as SPD Siamese Network. Firstly, we give an overview of the approach. Then, we give a summary of some previous approaches that we need in building our network. Finally, we explain our proposed method.

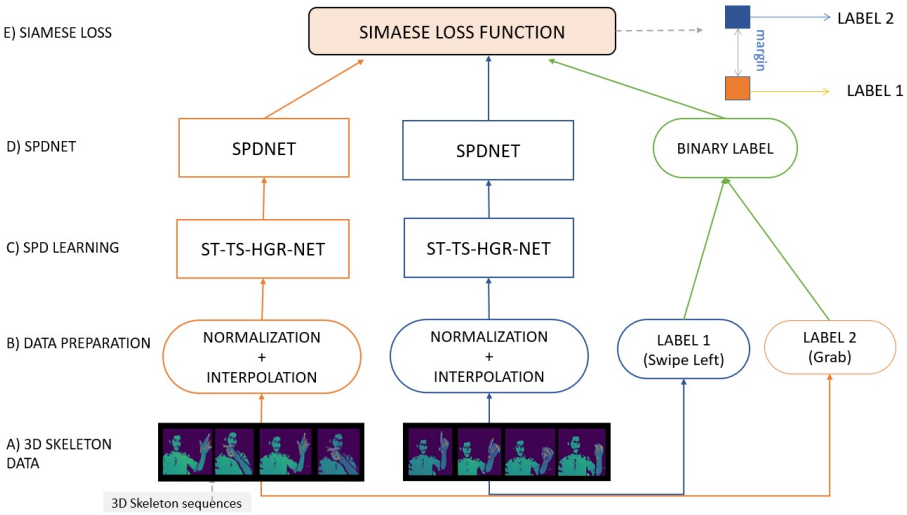


Figure 2: An overview of the proposed SPD Siamese network. Our method learns the SPD matrices from skeletal data. Using the Siamese network, the SPD matrices from different classes are distanced from each others. This distancing is used to predict hand gestures.

3.1 Overview

Our model, illustrated in Figure 2, aims to improve the performance of an SPD network for skeleton-based hand gesture recognition using the Siamese network. Before starting running the model, we have to make all the sequences the same number of frames using the interpolation method. The resulting arrays are normalized in order to facilitate the computing. The data is then ready to be executed. The proposed network is composed of three principal components: SPD learning features component, base SPD network component, and Siamese component. The initial input is an array describing the evolution of the 3D positions of the hand joints throughout the action time. For the learning of SPD matrices, we use two networks: Covariance SPD matrices (Huang and Van Gool, 2017) and the method called ST-TS-HGR-NET network proposed by (Nguyen et al., 2019) and used to learn the input data spatially and temporally returning an SPD matrix containing first-order information and second-order-information.

For the base SPD network component, we use the SPD network proposed by (Huang and Van Gool, 2017) in two different manners: with the transformation blocks and without the transformation blocks. Then, we twin the two previous components and use the Contrastive Loss function for training the model. Finally, we use the K-NN algorithm on the learnt model parameters applied to the base SPD network component for the classification.

3.2 SPD Matrix Learning

Among the methods to learn an SPD matrix-based representation from skeletal data, we work with first covariance matrix method which is easily computed and essentially with ST-TS-HGR-NET. This network architecture, as shown in Figure 3, is composed by four principal components: Convolution network, ST-GA-NET, TS-GA-NET and SPDC network.

Convolution Network: It highlights the correlation between the neighboring joints of the hand and learns the filter weight associated to each neighbor of a given joint. It takes as input a tensor $M_t \in \mathbb{R}^{5\times4\times3}$ describing 3D position of each joint of each finger. In order to facilitate the computation, we define $N_t \in \mathbb{R}^{6\times5\times3}$ as:

$$(N_t)_{i+1,j+1} = \begin{cases} (M_t)_{i,j} & if\ 2 \le i \le 4;\ 1 \le j \le 6 \\ 0 & else \end{cases} \quad (1)$$

Then, we apply a convolution operation without bias. Its kernel size is 3×3, the number of its input channels is 3 and the number of its output channels is d_l. The output of the convolution layer is $Y \in \mathbb{R}^{N\times5\times4\times d_l}$. The ST-GA-Net and the TS-GA-Net take as input the output of convolution layer and are executed simultaneously.

ST-GA-Net: Its principal objective is to learn spatially the hand joints positions of each frame and returns an SPD matrix containing first-order-information and second-order-information about the mean and the covariance of the spatial repartition of the frames. For this, we divided the input X coming out of the Convolution component to 6 sub-sequences

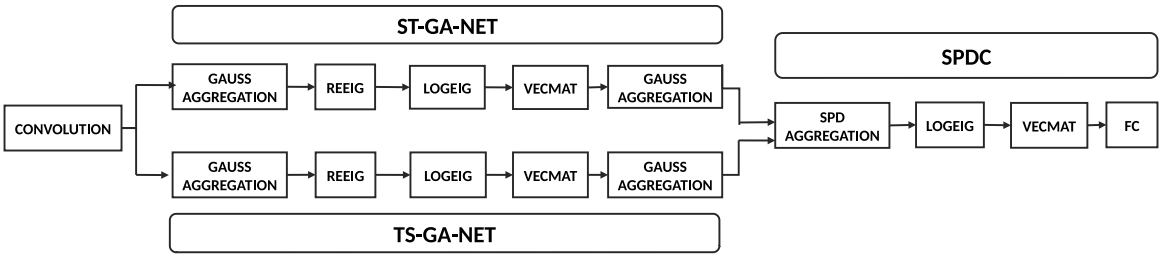


Figure 3: ST-TS-HGR-NET architecture. The network processes skeletal data spatially and temporally using the sub-networks ST-GA-NET and TS-GA-NET and returns an SPD matrix.

$(X_s)_{\{s=0..5\}}$ distributed as: the sub-sequence X_0 which describes all the frames of Y, each of X_1 and X_2 which describe one of the halves of all sequences of Y, and each of X_3, X_4 and X_5 which describe one third of all sequences of Y. The first layer, Gauss Aggregation Layer, returns as output:

$$Y(s,t,f) = \begin{bmatrix} cov_{s,t,f} + \mu_{s,t,f}\mu_{s,t,f}^T & \mu_{s,t,f} \\ \mu_{s,t,f}^T & 1 \end{bmatrix} \quad (2)$$

Where

$$\mu_{s,t,f} = mean_{4^{th}}\left(\frac{1}{4(2t_0+1)}\sum_{i=t-t_0}^{t+t_0} X_{s,t,f}\right) \quad (3)$$

$$cov_{s,t,f} = \frac{\sum_{j\in J_f}\sum_{i=t-t_0}^{t+t_0}(X_{s,i,j}-\mu_{s,t,f})(X_{s,i,j}-\mu_{s,t,f})^T}{4(2t_0+1)} \quad (4)$$

The ReEig Layer takes as input

$$X = \begin{bmatrix} X_0 & X_1 & X_2 & X_3 & X_4 & X_5 \end{bmatrix}^T \in \mathbb{R}^B, \quad B = 3N \times 5 \times (d_l+1) \times (d_l+1) \quad (5)$$

where $(X_s)_{s=0..5}$ are the outputs of the previous layer. It returns :

$$Y = U\ max(\varepsilon I, S)\ U^T \quad (6)$$

where $X = USV$ is the eigen-decomposition, I is the identity tensor (the same size as Z) and ε is a rectification threshold. This output is mapped into Euclidean space by the LogEig layer $(Y = log(X))$ and the VecMat layer (It takes the upper triangle part of an input X and vectorize them row by row and the output $Y \in \mathbb{R}^B$, $B = 3N \times 5 \times \frac{d_l(d_l+1)}{2} \times 1$). The second Gauss aggregation layer returns the last output $Y \in \mathbb{R}^B$, where $B = 6\times5\times(\frac{d_l(d_l+1)}{2}+1)\times(\frac{d_l(d_l+1)}{2}+1))$ of the $ST-GA-NET$ component, given by:

$$Y(s) = \begin{bmatrix} cov(s) + \mu_s\,\mu_s^T & \mu_s \\ \mu_s^T & 1 \end{bmatrix} \quad (7)$$

Where N_s is the number of frames of X_s, mean(s) and cov(s) are defined as:

$$\mu_s = mean_{2^{nd}}(X_s) \quad (8)$$

$$cov_s = cov_{2^{nd}}(X_s) \quad (9)$$

TS-GA-Net: Its role consists to capture temporal information of each hand joint. Each sequence Y (output of the convolution layer) is divided to 6 subsequences $\{X_s\}$ in the same manner as in the previous component. Each sub-sequence is divided into K sub-sequences. We obtain the set of sub-sequences $\{Z_{s,k}\}_{s=0...5,k=0...K-1}$ where $Z_{s,k}$ refers to k^{th} the subsequence of X_s. The outputs of the first Gauss Aggregation Layer are in $\mathbb{R}^B$, $B = 6\times5\times K\times4\times(d_l+1)\times(d_l+1)$ and are estimated as:

$$Y(s,k) = \begin{bmatrix} cov_{s,k,f} + \mu_{s,k,f}\,\mu_{s,k,f}^T & \mu_{s,k,f} \\ \mu_{s,k,f}^T & 1 \end{bmatrix} \quad (10)$$

Where:

$$\mu_{s,k,f} = mean_{2^{nd}}(Z_{s,k}) \quad (11)$$

$$cov_{s,k,f} = cov_{2^{nd}}(Z_{s,k}) \quad (12)$$

The outputs of the ReEig, the LogEig and the VecMat Layers are computed in the same manner as that of ST-HGR-Net. For the second Gauss Aggregation Layer, the output $Y \in \mathbb{R}^{6\times5\times(\frac{d_l(d_l+1)}{2}+1)\times(\frac{d_l(d_l+1)}{2}+1)}$ of the ST-GA-NET component, given by:is computed as:

$$Y = \begin{bmatrix} cov + \mu\,\mu^T & \mu \\ \mu^T & 1 \end{bmatrix} \quad (13)$$

Where:

$$\mu = mean_{2^{nd},4^{th}}(Y) \quad (14)$$

$$cov = cov_{2^{nd},4^{th}}(Y) \quad (15)$$

SPDC NET: In the first Layer, SPD Aggregation takes both outputs of ST−GA−NET and TS−GA−NET and returns as output

$$Y = \sum W_i X_i W_i^T \quad (16)$$

Where its parameter $W_i \in \mathbb{R}^{d_c\times(\frac{d_l(d_l+1)}{2}+1)}$ is a Stiefel weight parameter.

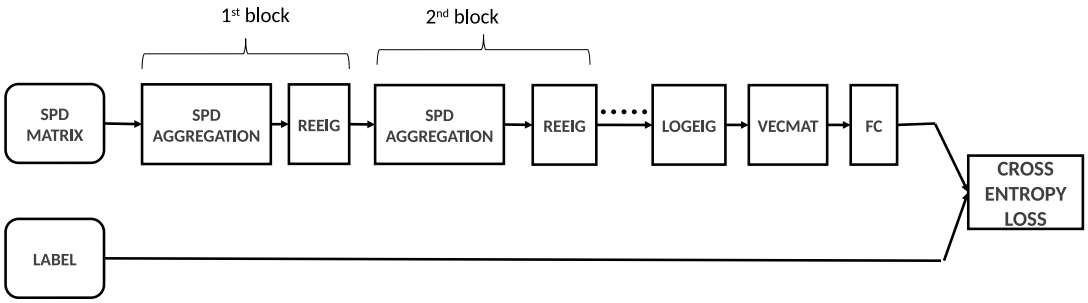


Figure 4: SPDNET architecture. The model is used to process the input SPD matrices, map them and predict the actions of the hand.

Then, we map the SPD Aggregation output using a LogEig layer and VecMat layer. Besides, we apply a fully connected layer and a SoftMax layer. Finally, we use the Cross Entropy Loss to calculate the loss function.
For details, we refer readers to (Nguyen et al., 2019).

3.3 Classification using SPD NET

After learning the SPD matrices, comes the step of classification using the learnt features in gesture classification. Wherefore, we use the architecture model proposed by (Huang and Van Gool, 2017) and illustrated in Figure 4. It created a neural SPD network based on succession of SPD transformation blocks which aims to generate more compact and discriminative SPD matrices, each block is composed of a BiMap layer (equivalent to SPD Aggregation layer) and a Rectified layer and finalized his SPD architecture by mapping to a flat space with the matrix logarithm operation $\log(\cdot)$ on the SPD matrices. Then, we utilize a fully connected layer for the classification.

3.4 SPD Siamese Network

This SPD Siamese network, illustrated in Figure 5, consists of two identical SPD sub-networks joined at their outputs. During training the two sub-networks extract features from two signatures, while the joining neuron measures the distance between the two feature vectors (Bromley et al., 1993). That's why, before starting the execution of the Siamese model, we need to create an equal number of positive pairs SPD matrices (from the same class) and negative pairs (from different classes) out of the total learnt SPD matrices. SPD Siamese network input takes as an input target the binary label BL defined as:

$$BL = \delta_{m,n} \tag{17}$$

Where m is the class of the first input and n is the class of the second one. Let Y_1 and Y_2 be the outputs of the two twin SPD sub-networks and m be the margin parameter. The Contrastive Loss function is given by the following expression:

$$\begin{aligned} L_{Siamese}(Y_1,Y_2,BL) &= BL\ \|Y_1-Y_2\|_2 \\ &+ (1-BL)\ max\,(0, m-\|Y_1-Y_2\|_2) \end{aligned} \tag{18}$$

The interest of using Contrastive Loss function is her discriminative properties since it minimizes distance between positive pair and makes negative pairs m distant from each other. That improves discriminative performance and helps in gesture recognition.

That's why, the SPD Siamese network performances depend heavily on the SPD sub-network taken as a base classification model and the convenient choice of the margin parameter of the Contrastive Loss function.

3.5 Hand Gesture Recognition

We are going to use the learnt weights of the SPD network after training the SPD Siamese network. Let N be the number of gesture classes. Since Siamese Network doesn't give a direct prediction of data class, we are going to use K-Nearest Neighbor algorithm (K =1) for classification. We choose randomly N items $(X_{rep}^{(k)})_{k=1..N}$: one item per class. Let X be an item with unknown class, Y be the output of the SPD network with X as input, $Y_{rep}^{(k)}$ the output of the SPD Network with $X_{rep}^{(k)}$ as input. The class of item x is determined using the following formula:

$$class\,(X) = \min_{k\in[1..N]} \left\| Y - Y_{rep}^{(k)} \right\|_2 \tag{19}$$

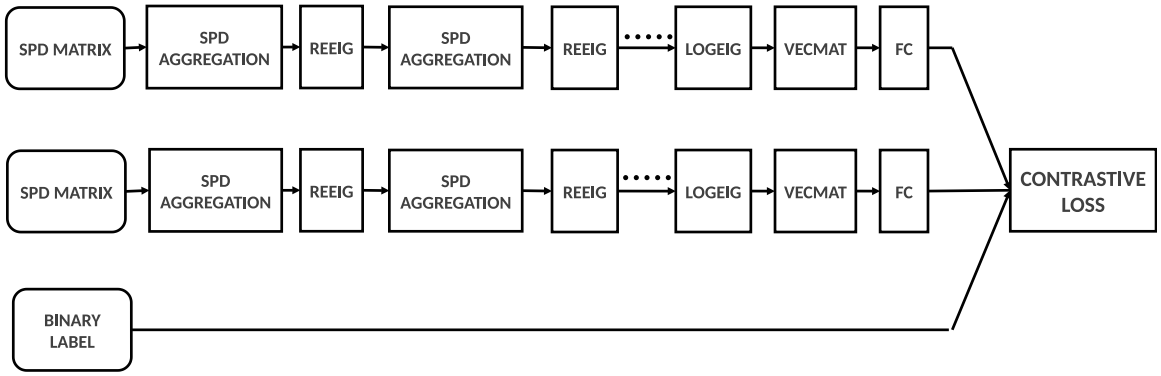


Figure 5: Siamese Network architecture using SPDNET as a sub-network.

4 EXPERIMENTS AND RESULTS

We have implemented and evauated SPD Siamese network in DHG dataset. For the SPD learning network using ST-TS-HGR-NET architecture (Nguyen et al., 2019), the sequences are normalized, interpolated into 500 frames. We set t_0 = 1, K=15, ε = 1e-4, $d_l = 9$, $t_0 = 1$, K=15, $d_l = 9$ and $d_c = 200$ (For more details,we refer readers to (Nguyen et al., 2019) and (Huang and Van Gool, 2017)).

We presented results with the SPD model ST−TS−HGR−NET. The optimizer used is Adam optimizer with learning rate lr = 1e-4 (after training the model with various learning rates, we found that using a learning rate lr = 1e-4 gives a rapid convergence) . We trained this network for 15 epochs (24 min/epoch). For the Siamese Network and the SPDNet network, we used Adam optimizer with learning rate lr = 7e-4. We trained this network for 500 epochs (1min/epoch). We evaluated the approaches mentioned in this paper using DHG dataset 2017 with 14 classes and 28 classes.

All the results are available in the Github repository as well as the code to reproduce our method at:

https://github.com/Mohamed-Sanim300/SPD_Siamese_Network.

4.1 Dataset

DHG dataset (De Smedt et al., 2017) contains depth images and hand skeletons captured by "the Intel RealSense short range depth camera" (30 frames per second). The dataset contains sequences of 14 hand gestures performed in two ways: using one finger and the whole hand.

The gestures are listed in Table 1. An example a swipe left gesture is illustrated in Figure 6.

We can consider the dataset to have 14 gestures regardless of how they are performed. It can be considered as having 28 gestures, considering that each of the two ways of accomplishing each gesture is an independent action. Each frame of sequences contains a depth image, the coordinates of 22 joints both in the 2D depth image space and in the 3D world space forming a full hand skeleton.

Figure 6: Example of a swipe left gestures from the training dataset.

Table 1: List of the gestures included in the dataset.

Reference	Name	Type
1	Grab	Fine
2	Tap	Coarse
3	Expand	Fine
4	Pinch	Fine
5	Rotation Clockwise	Fine
6	Rotation Counter Clockwise	Fine
7	Swipe Right	Coarse
8	Swipe Left	Coarse
9	Swipe Up	Coarse
10	Swipe Down	Coarse
11	Swipe X	Coarse
12	Swipe +	Coarse
13	Swipe V	Coarse
14	Shake	Coarse

We are going to use the 3D skeletal world space. It has been split into 1960 train sequences (70% of the dataset) representing the gestures performed by the subjects 2, 3, 4, 7, 8, 9, 10, 11, 12, 13, 14, 15,

16, 19, 20, 21, 22, 25, 26, 27 and 840 test sequences captured with the help of the other volunteers (30% of the dataset). The DHG dataset is well balanced. For train sequences of DHG-14, We have between 130 and 150 skeleton sequences per gesture and for DHG-28 training items, we have between 64 and 74 skeleton sequences per gesture.

4.2 Experimental Settings

As mentioned in section 3.4, SPD Siamese depends on the given margin and the SPD network i.e., the weights parameters of the SPD transformation block. First of all, we are going to compare the network before and after introducing Siamese network. Then we are going to examine the influence of margin variation and to choose the most efficient SPD network structure.

4.2.1 Importance of the Introducing of Siamese Network

In this experiment, we execute, without introducing Siamese network, the SPD learning networks: ST-TS-HGR-NET. Then, we try the execution with Siamese model and compare the obtained accuracy results. The SPD network is SPDNET without transformation blocks. According to Table 2, it's obvious that the performance of the model has been improved even though it has already achieved a very high score (>91%). This explains the importance of our new approach.

Table 2: Recognition accuracy with/without Siamese Network introducing.

Dataset	Without Siamese (%)	With Siamese (%)
DHG-14	91.07	**95.60**
DHG-28	87.62	**94.05**

4.2.2 SPD Network

We study the behavior of Siamese network towards different depth of SPD network (depth = 0,1,3) and we evaluate the performance of each network. The results of this experiment illustrated in Table 3 shows that it's more efficient to use the SPDNET without any transformation block while working with Siamese because the SPD matrix, output of the SPD learning model, the best for representing gestures since it contains various information(mean, covariance...) about the gesture performance in different states over time.

Table 3: Recognition accuracy for different SPD networks on DHG dataset using 14 gestures. TB is an abbreviation of transformation block.

SPD Network	Accuracy on DHG-14(%)
SPDNET + 3 TB	85.59
SPDNET + 1 TB	89.40
SPDNET + 0 TB	**95.60**

4.2.3 Margin of the Contrastive Loss Function

In this experiment, we vary the margin m and keep other components of our network unchanged (ST-TS-HGR-NET for the SPD learning network and SPDNET + 0 block for the SDP network). Table 4 shows the variation of performance as a function of the margin m used in the Contrastive Loss function (m = 1, 2, 5, 7, 8, 10, 20). According to the given results, the performance of our model is constantly improving until it reaches its maximum at margin = 7 and then begins to decline gradually.

Table 4: Recognition accuracy for different settings of the margin.

Margin	Accuracy on DHG-14(%)	Accuracy on DHG-28(%)
1	91.78	87.62
2	92.02	88.45
5	92.5	90.48
7	**95.60**	**94.05**
8	93.09	91.78
10	93.09	88.45
20	91.54	85.48

For the following section, we report results given by the SPDNET+0 block with margin = 7.

4.3 Comparison with State-of-the-Art

The Table 5 summarizes the other approaches using 3D skeletal hand sequences of DHG-14/28 dataset and the performance obtained by each of them. The given results confirm the effectiveness of the proposed network architecture for hand gesture recognition. We get the higher results compared to other methods.
Based on the presented results, it can be concluded that our approach which can be considered as a combination between the SPDNET invented by (Huang and Van Gool, 2017), the ST−TS−HGR−NET proposed by (Nguyen et al., 2019) and Siamese network explained in (Koch et al., 2015), provides an advantage compared to previous works. This can be explained as follows:

- This approach is robust for the class imbalance: using the base model, a single data per class

Table 5: State-of-the-art methods on DHG dataset.

Method	Accuracy on DHG-14(%)	Accuracy on DHG-28(%)
RNN (Chen et al., 2017)	84.68	80.32
SoCJ + HoHD + HoWR (De Smedt et al., 2016)	88.24	81.9
STA-Res-TCN (Hou et al., 2018)	93.57	90.7
TCN-Summ (Sabater et al., 2021)	93.57	91.43
ST-TS-HGR-NET (Nguyen et al., 2019)	94.29	89.4
DD-Net (Yang et al., 2019)	94.6	91.9
Our SPD Siamese Network	**95.60**	**94.05**

is enough for the network to recognize the data classes in the future.

- Due to the feature of distinguishing between the differences and bringing the similarities closer, it gives a very high accuracy result (95.60%)

Thanks to these characteristics, we succeed to propose a new approach that outperforms even the approaches that were the basis of our approach.

5 CONCLUSION

In this work, we presented a new approach for hand gesture recognition using skeletal data. The proposed method consists of learning SPD matrix coupled to the use of Siamese network. We have evaluated the proposed approach on DHG 14/28 Dataset. The achieved results show high accuracy outperforming state-of-the-art methods.

As future work, we plan to study the impact of using geodesic distance on the SPD matrix within Siamese network. Besides, we intend to focus on online recognition systems using short time sliding windows where we could recognize gestures. Finally, applying our approach on different datasets and different applications such as human action recognition could be interesting to study its performance on different context.

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