Generative vs. Discriminative Deep Belief Netwok for 3D Object Categorization

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Abstract: Object categorization has been an important task of computer vision research in recent years. In this paper, we propose a new approach for representing and learning 3D object categories. First, We extract the Viewpoint Feature Histogram (VFH) descriptor from point clouds and then we learn the resulting features using deep learning architectures. We evaluate the performance of both generative and discriminative deep belief network architectures (GDBN/DDBN) for object categorization task. GDBN trains a sequence of Restricted Boltzmann Machines (RBMs) while DDBN uses a new deep architecture based on RBMs and the joint density model. Our results show the power of discriminative model for object categorization and outperform state-of-the-art approaches when tested on the Washington RGBD dataset.

1 INTRODUCTION

With the advent of new 3D sensors like Microsoft Kinect, 3D perception became a fundamental vision research in mobile robotic applications like scene manipulation or grasping, scene understanding, and 3D point cloud classification. The Point Cloud Library (PCL) was developed by Rusu *et al.* (Rusu and Cousins, 2011) in 2010 and was officially published in 2011. This open source library, licensed under Berkeley Software Distribution (BSD) terms, represents a collection of state-of-the-art algorithms and tools that operate with 3D point clouds. Several studies have been made based on PCL detectors and descriptors, allowing for 3D object recognition applications. PCL integrates several 3D detectors as well as 3D local and global descriptors. In 3D local descriptors, each point is described by its local geometry. They are developed for specific applications such as object recognition, and local surface categorization. This local category includes Signature of Histograms of OrienTation (SHOT) (Tombari et al., 2010), Point Feature Histograms (PFH) (Rusu et al.,), Fast Point Feature Histograms (FPFH) (Rusu et al., 2009), SHOTCOLOR (Tombari et al., 2011), and so on. On the other hand, the 3D global descriptors describe object geometry and they are not computed for individual points, but for a whole cluster instead. The global descriptors are high-dimensional representations of object geometry. They are usually calculated for subsets of the point clouds that are likely to be objects. The global category encodes only the shape information and includes Viewpoint Feature Histogram (VFH) (Rusu et al., 2010), Clustered Viewpoint Feature Histogram (CVFH) (Aldoma et al., 2011), CVFH (OUR-CVFH) (Aldoma et al., 2012), and Ensemble of Shape Functions (ESF) (Wohlkinger and Vincze, 2011).

The ability to identify or recognize 3D objects is highly valuable for performing imperative tasks in mobile robotics. Machine learning techniques are applied for this task which include Support Vector Machines (SVMs) (LeCun et al., 2004) (Zhang et al., 2006) (Janoch et al., 2013), Nearest Neighbor (NN) (McCann and Lowe, 2012), Hidden Markov Model (HMM) (Torralba et al., 2003), and Artificial Neural Network (ANN) (Basu et al., 2010).

The origin of ANN dates back to efforts for finding a mathematical representation for information processing in human brains. The brain consists of a large number of processing units (10^{11} units according to (Azevedo et al., 2009)) which operate in parallel and are highly inter-connected. ANN are designed in a similar manner using a large number of process-

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ing units called perceptrons that operate in the parallel process. Research on ANN discover some limitations of the capability of perceptrons and invent multilayer perceptron (MLP) neural networks (Rumelbart and McClelland, 1986). Unfortunately, MLP also shows the limitations for some complex nonlinear functions that cannot be efficiently represented by this type of networks. In (Serre et al., 2007), authors show the evidence that the brain of a mammal is organized in the form of a deep architecture. A specified input is characterized at various levels of abstraction, where every level relates to a diverse area of cortex. Researchers used the deep architecture concept in neural networks for training new deep multi-layer neural networks which are stimulated by the biological depth of brain. Such deep models involve numerous layers and parameters that require learning through the complex process. To deal with this problem, the authors in (Hinton et al., 2006a) suggest a deep belief network (DBN) with multiple layers of hidden units.

DBN is a graphical model consisting of undirected networks at the top hidden layers and directed networks in the lower layers. The learning algorithm uses greedy layer-wise training by stacking restricted Boltzmann machines (RBM) which contain hidden layer for modeling the probability distribution of perceptible variables. The idea of having multiple hidden layers is that the preceding hidden layer acts as the visible layer for the next hidden layer and thus the model can incrementally learn more complex features of data.

In general, deep learning architectures can be broadly classified into three main categories (Deng, 2014):

1. Generative deep architectures: the aim is to characterize the high-order correlation properties of the visible data for pattern analysis or synthesis purposes, and/or characterize the joint statistical distributions of the visible data and their associated classes;
2. Discriminative deep architectures: the aim is to directly provide discriminative power for pattern classification, often by characterizing the posterior distributions of classes conditioned on the visible data;
3. Hybrid deep architectures: the aim is to combine the power of discrimination with the outputs of generative architectures via better optimization or/and regularization.

Our work focuses on 3D object categorization for mobile robotic grasping. First, we extract Viewpoint Feature Histogram (VFH) descriptors that encode geometric features of 3D point clouds followed by learning the resulting features using effective deep architectures. We evaluate both generative and discriminative deep belief network (GDBN/DDBN) using different RBM training techniques which include Contrastive Divergence (CD), Persistent Contrastive Divergence (PCD), and Free Energy in Persistent Contrastive Divergence (FEPCD).

The main contributions of our paper are:

- We propose a new 3D object categorization pipeline based on VFH descriptor and deep learning architectures;
- We compare the extracted features with GDBN and DDBN architectures in order to show the difference between generative and discriminative models for object categorization.

The rest of the paper is organized as follows. In Section 2 we review previous works. In Section 3 we give a brief description of VFH descriptor. In Section 4 we present an overview of our proposed approach. In Section 5 two different deep learning architectures are illustrated. And in Section 6, the experimental results carried out to demonstrate the functionality and usability of this work are presented. Finally, in Section 7 the main conclusions and future works are outlined.

2 PREVIOUS WORK

Most of the recent work on 3D object categorization have focused on appearance, shapes, and Bag of Words (BoW) extracted from certain viewing point changes of the 3D objects. In (Toldo et al., 2009), authors introduce Bag of Words (BoW) approach for 3D object categorization. They use spectral clustering to select seed-regions then compute the geometric features of the object sub-parts. Vector quantization is applied to these features in order to obtain BoW histograms for each mesh. Finally, Support Vector Machine is used to classify different BoW histograms for 3D objects. In (Nair and Hinton, 2009), a top-level model of Deep Belief Networks (DBNs) is presented for 3D object recognition. This model is a third-order Boltzmann machine that is trained using a combination of both generative and discriminative gradients. The model performance is evaluated on NORB images where the dimensionality for each stereo-pair image is reduced by using a foveal image. The final representation consists of 8976-dimensional vectors that are learned with a top-level model for Deep Belief Nets (DBN). In (Bo et al., 2011), a set of kernel features is introduced for object recognition. The authors develop kernel descriptors on depth maps that model size, depth edges, and 3D shape. The main match kernel framework defines pixel attributes, designs match kernels in order to measure the similarities of image patches and then determines low dimensional match kernels. In (Lai et al., 2011a), the authors build a new RGBD dataset and propose methods to recognize and detect RGBD objects. They use SIFT descriptor to extract visual features and spin image descriptor to extract shape features that are used for computing efficient match kernel (EKM). Finally, linear support vector (LiSVM), gaussian kernel support vector machine (kSVM) and random forest (RF) are trained to recognize both the category and the instance of objects. In (Madry et al., 2012), the authors propose the Global Structure Histogram (GSH) in order to describe the point cloud information. The approach encodes the structure of local feature response on a coarse global scale to retain low local variations and keep the advantage of global representativeness. GSH can be instantiated in partial object views and learned using complete or incomplete information about an object. In (Socher et al., 2012), the authors introduce the first convolutional-recursive deep learning model for 3D object recognition. They compute a single CNN layer to extract low-level features from both color and depth images. Then, these representations are provided as input to a set of RNNs with random weights that produce high-quality features. Finally, The concatenation of all the resulting vectors forms the final feature vector for a softmax classifier. The authors in (Schwarz et al., 2015) develop a meaningful feature set that results from the pre-trained stage of Convolutional Neural Network (CNN). The depth and RGB images are processed independently by CNN and the resulting features are then concatenated to determine the category, instance, and pose of the object. In (Alexandre, 2016), author proposes a new approach for RGBD object classification. Four independent Convolutional Neural Networks (CNNs) are trained, one for each depth data and three for RGB data and then trains these CNNs in a sequence. The decisions of each network are combined to obtain the final classification result. The authors of (Ouadiay et al., 2016) propose a new approach for real 3D object recognition and categorization using Deep Belief Networks. First, they extract 3D keypoints from point clouds using 3D SIFT detector and then they compute SHOT/SHOTCOLOR descriptors. The performance of the approach is evaluated on two datasets: Washington RGBD object dataset and real 3D object dataset.

3 METHOD OVERVIEW

In this work, we use the VFH descriptor to describe the set of 3D point clouds and then we extract the geometric features which are considered as the input layer x of GDBN and DDBN architectures. The input layer has a number N of units which is equivalent to the quantity of sample data x (308). Finally, we fix three hidden layers in both GDBN and DDBN architectures. Figure 1 summarizes the main steps of our approach.

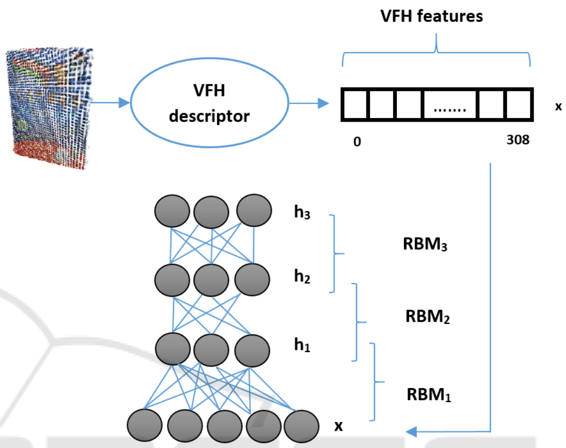


Figure 1: Our proposed approach for 3D object categorization.

The general approach is achieved as follows:

1. Extract geometric features for all training set using VFH descriptor;
2. Input layer x takes the extracted geometric features;
3. Train RBMs using CD, PCD or FEPCD training (see Section 5.3):
   - training the first RBM;
   - training the second RBM using the training data resulting from the first RBM learning;
   - training the third RBM: for GDBN architecture, RBM is generative. Whereas for DDBN architecture, we train a joint density model through discriminative RBM and then each conceivable label is tested with a test vector. The label which contains the least energy is selected as the best corresponding class.
4. Use the back-propagation technique through the whole classifier to fine-tune the weights for an optimal classification.

4 POINT CLOUD PROCESSING

4.1 Point Clouds

The point cloud is a data structure which represents three-dimensional data. In 3D cloud, the points are usually described by their x, y and z geometric coordinates of a sampled surface. When the point cloud contains the color information, the structure becomes four-dimensional data. Point clouds can be obtained using stereo cameras, 3D laser scanners, Time-of-flight cameras or Kinect.

In 3D space, points are defined in a clockwise reference frame that is centered at the intersection of the optical axis with the plane which contains the front wall of the camera. The reference frame is decomposed as follows:

- x-axis: is horizontal and directed to the left;
- y-axis: is vertical and faces up;
- z-axis: coincides with the optical axis of the camera. It is turned towards the object.

4.2 Washington RGBD Dataset

Washington RGBD dataset is a large dataset built for 3D object recognition and categorization applications. It is a collection of 300 common household objects which are organized into 51 categories. Each object is placed on a turntable and is captured for one whole rotation in order to obtain all object views using Kinect camera that records synchronized and aligned 640x480 RGB and depth images at 30 Hz (Lai et al., 2011b).

4.3 Viewpoint Feature Histogram (VFH)

The global descriptors are high-dimensional representations of object geometry. They are more efficient in object recognition, geometric categorization, and shape retrieval. Global descriptors describe object geometry. They are not computed for individual points, but for a whole cluster.

The viewpoint feature histogram (VFH) (Rusu et al., 2010) computes a global descriptor of the point cloud and consists of two components:

1. a surface shape component;
2. a viewpoint direction component.

VFH aims to combine the viewpoint direction directly into the relative normal angle calculation in the FPFH descriptor (Rusu et al., 2009). The viewpoint-dependent component of the descriptor is a histogram

Figure 2: A sample of selected point clouds from Washington RGBD dataset.

of the angles between the vector $(p_c - p_v)$ and each point's normal. This component is binned into a 128-bin histogram. The other component is a simplified point feature histogram (SPFH) estimated for the centroid of the point cloud and an additional histogram of distances of all points in the cloud to the cloud's centroid.

The three angles (α, ϕ, θ) with the distance d between each point and the centroid are binned into a 45-bin histogram. The total length of VFH descriptor is the combination of these two histograms and is equal to 308 bins.

5 DEEP LEARNING ARCHITECTURES

In this section, we briefly introduce both Generative and Discriminative Deep Belief Network (GDBN/DDBN) architectures. We also illustrate the difference between the Generative and Discriminative restricted Boltzmann machine (GRBM/DRBM) which constitute many layers in DBN architecture.

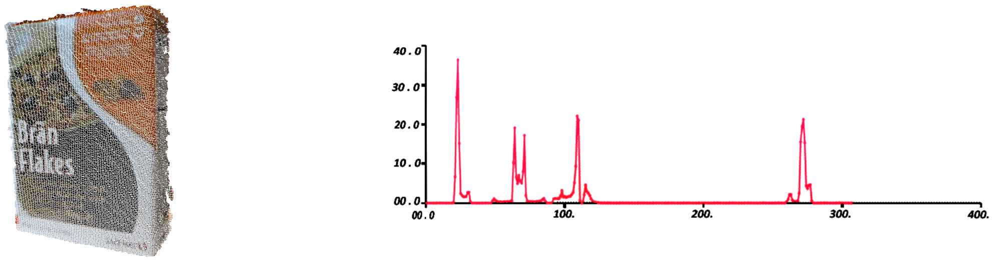


Figure 3: (a) 3D point cloud of food box. (b) VFH descriptor of food box point cloud: x-axis represents a number of histogram bin and y-axis represents a percentage of points falling in each bin.

5.1 Generative Deep Belief Network (GDBN)

5.1.1 Restricted Boltzmann Machines (RBMs)

Restricted Boltzmann Machines (RBMs) (Smolensky, 1986) are a specific category of energy based model which include hidden variables. RBMs are restricted in the sense so that no hidden-hidden or variable-variable connections exist. The architecture of a generative RBM is illustrated in Figure 4.

RBMs are a parameterized generative stochastic neural network which contain stochastic binary units on two layers: the visible layer and the hidden layer.

1. Visible units (the first layer): they contain visible units (x) that correspond to the components of an observation (i.e. VFH descriptors in this case of study);
2. Hidden units (the second layer): they contain hidden units (h) that model dependencies between the components of observations.

The stochastic nature of RBMs results from the fact that the visible and hidden units are stochastic. The units are binary, i.e. $x_i, h_j \in \{0,1\} \forall\ i$ and j, and the joint probability which characterize the RBM configuration is the Boltzmann distribution:

$$p(x,h) = \frac{1}{Z} e^{-E(x,h)} \qquad (1)$$

The normalization constant is $Z = \sum_{x,h} e^{-E(x,h)}$ and the energy function of an RBM is defined as:

$$E(x,h) = -b^{'}x - c^{'}h - h^{'}Wx \qquad (2)$$

where:

- W represents the symmetric interaction term between visible units (x) and hidden units (h);
- b and c are vectors that store the visible (input) and hidden biases (respectively).

RBMs are proposed as building blocks of multi-layer learning deep architectures called deep belief networks. The idea behind is that the hidden neurons extract pertinent features from the visible neurons. These features can work as the input to another RBM. By stacking RBMs in this way, the model can learn features for a high-level representation.

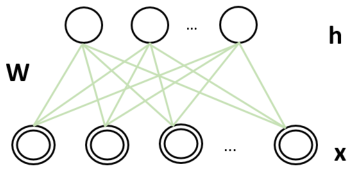


Figure 4: Generative RBM model. The visible units x and hidden units h are connected through undirected and symmetric connections. There are no intra-layer connections.

5.1.2 GDBN Architecture

Deep Belief Network (DBN) is the probabilistic generative model with many layers of stochastic and hidden variables. In (Hinton et al., 2006b), the authors introduce the motivation for using a deep network versus a single hidden layer (i.e. a DBN vs. an RBM). The power of deep networks is achieved by having more hidden layers. However, one of the major problems for training deep network is how to initialize the weights W between the units of two consecutive layers ($j-1$ and j), and the bias b of layer j. Random initializations of these parameters can cause poor local minima of the error function resulting in low generalization. For this reason, Hinton *et al.* introduced a DBN architecture based on training sequence of RBMs. DBN train sequentially as many RBMs as the number of hidden layers that constitute its architecture, i.e for a DBN architecture with l hidden layers, the model has to train l RBMs. For the first RBM, the inputs consist of the DBN's input layer (visible units) and the first hidden layer. For the second RBM, the inputs consist of the hidden unit activations of the previous RBM and the second hidden layer. The same holds for the remaining RBMs to browse through the l layers. After the model performs this layer-wise algorithm, a good initialization of the biases and the hidden weights of the DBN is obtained. At this stage, the model should determine the weights from the last hidden layer for the outputs. To obtain a successfully supervised learning, the model ”fine-tunes” the resulting weights of all layers together. Figure 5 illustrates a generative DBN architecture with one visible layer and three hidden layers.

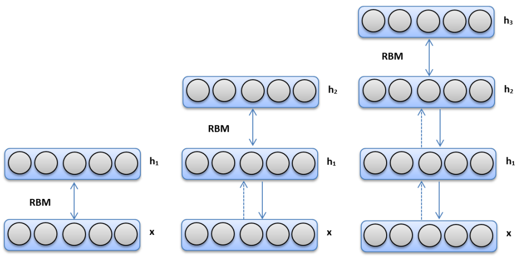


Figure 5: Generative DBN architecture (GDBN).

5.2 Discriminative Deep Belief Network (DDBN)

5.2.1 Discriminative Restricted Boltzmann Machines (DRBMs)

RBMs are used as generative models for various applications. They use a layer of hidden variables for modeling the scattering over visible variables. Those models are typically trained only for modeling the inputs of a classification task. They are also capable of modeling the joint distribution of the inputs and their associated target classes similar to the last layer of a DDBN (see 7). We are interested in such joint models for a classification application.

In this work (Larochelle and Bengio, 2008), the authors propose a Discriminative Restricted Boltzmann Machines which aim to train a density model by means of a particular RBM consisting of two sets of visible elements. RBM acts as a parametric model of joint distribution among a layer of hidden variables $h = (h_1, \ldots, h_n)$ and the visible variables of the inputs $x = (x_1, \ldots, x_d)$ and the target y, that is defined as:

$$p(y,x,h) \propto e^{-E(y,x,h)} \tag{3}$$

where

$$E(y,x,h) = -h^{'}Wx - b^{'}x - c^{'}h - d^{'}\vec{y} - h^{'}U\vec{y} \tag{4}$$

with $\Theta = (W,b,c,d,U)$ is the set of parameters and $\vec{y} = (1_{y=i})_{i=1}^{c}$ for C classes.

5.2.2 DDBN Architecture

DDBN architectures have been proposed for different applications (Zhou et al., 2010) (Liu et al., 2011). In our work, we use a learning algorithm; discriminative deep belief network (DDBN) based on discriminative restricted Boltzmann machine (DRBM) as defined in (Keyvanrad and Homayounpour, 2014).

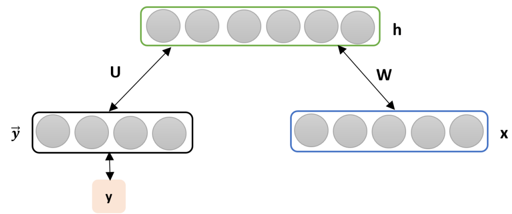


Figure 6: Discriminative RBM model (DRBM). RBM modeling the joint distribution of inputs x and target class y (represented as one-hot vector by $\vec{y}$) from (Larochelle and Bengio, 2008). Hidden units are denoted by h.

DBN aims at letting every RBM model in the structure to obtain a diverse representation of data. In other words, after RBM is trained, the activity values from the hidden units act as the training data for a higher-level RBM learning.

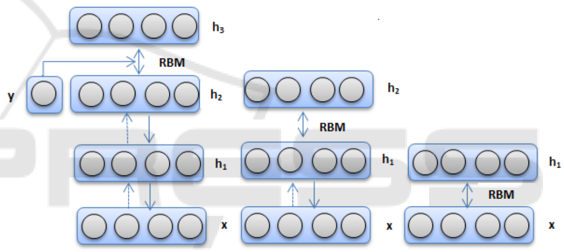


Figure 7: Discriminative DBN architecture (DDBN). The last RBM models the joint distribution of inputs x and target class y. Hidden units are denoted by h.

In DDBN, we need to use a DRBM in the last layer as a classifier for obtaining labels from the input data. The input layer has a N number of units which is equivalent to the quantity of sample data x. The label layer has C representing y as the number of classes. DDBN trains a joint density model through discriminative RBM and then each conceivable label is tested with a test vector. The label which contains the least energy is selected as the best corresponding class. Afterward, we use the back-propagation technique through the entire classifier for fine-tuning the weights for optimal classification.

5.3 Training in GRBM/DRBM

5.3.1 Contrastive Divergence (CD)

CD is the most popular gradient approximation algorithm. CD initializes the Markov chain with a training data then the binary hidden units are computed. Once the method defines binary hidden unit states then the visible values are recalculated. Lastly, the probability of hidden unit instigations is calculated by means of hidden and visible unit's values (Carreira-Perpinan and Hinton, 2005) .

5.3.2 Persistent Contrastive Divergence (PCD)

As the CD sampling has a few drawbacks and is not precise, PCD method is proposed so that only the last chain state is used in the preceding update step (Tieleman, 2008).

5.3.3 Free Energy in Persistent Contrastive Divergence (FEPCD)

Numerous insistent chains can be utilized in parallel during PCD sampling and can mention the present state as fantasy points in each of these chains. However, there is a blind chain selection and it's not necessary that the best one is always selected. Recently, (Keyvanrad and Homayounpour, 2014) proposed a new sampling method that defines a standard for the goodness of chain. This method employs free energy as a measure to acquire best samples from the generative model that are able to precisely calculate the gradient of log probability from training data.

6 EXPERIMENTAL RESULTS

In this section, we tested our categorization approach on Washington RGBD dataset. The training and testing sets contain 14800 point clouds that are computed using a Xeon(R) 3.50 GHz CPU 32 GB RAM and K2000 Nvidia card on Ubuntu 14.04. Figure 2 shows the examples of 3D point clouds from our training set.

Table 1: GDBN/DDBN characteristics that are used in our experiment.

Characteristics	Value
Hidden layers	3
Hidden layer units	300-300-1500
Learn rates	0.3
Epochs	200
Input layer units	size of VFH descriptor (308)

We use a GDBN/DDBN with one visible layer that contains the VFH descriptors of all training sets, as well as three hidden layers in order to define a 308-300-300-1500 GDBN/DDBN structures. Then, we train the weights of each layer separately with the fixed number of epochs equal to 200 (see Table 1).

6.1 Evaluation of Generative Model: GDBN

GDBN aims at allowing each RBM model in the sequence to receive a different representation of the data. In other words, after RBM is trained, the activity values of its hidden units are used as the training data for learning a higher-level RBM. As a comparison, we evaluate the training process of GDBN using CD, PCD or FEPCD training methods. Table 2 shows that the classification error decreases with the FEPCD training method. We can also remark that FEPCD training method presents the best accuracy value. The best training performance indicates the iterations at which the validation performance reaches a minimum mean squared normalized error which is defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2 \tag{5}$$

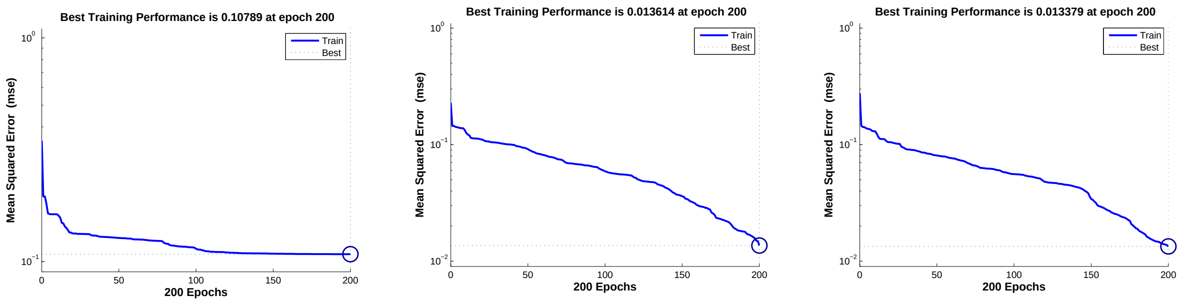
With: $\hat{Y}_i$ is a vector of n predictions, and Y_i is the vector of observed values. As shown in Figure 8, the best performance is obtained with FEPCD training.

Table 2: Classification error and accuracy on Washington RGBD dataset for 308-300-300-1500 GDBN structure using different training methods: CD, PCD and FEPCD.

	Error	Acc.
GDBN-CD	0.6549	34.51%
GDBN-PCD	0.0250	97.5%
GDBN-FEPCD	0.0206	97.9%

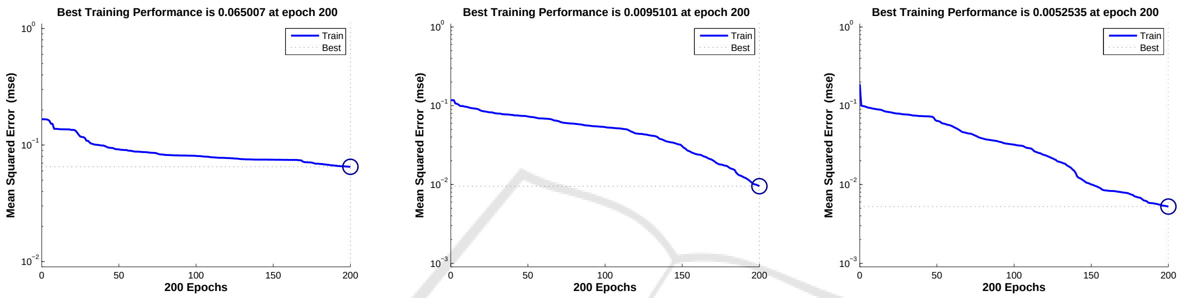
6.2 Evaluation of Discriminative Model: DDBN

The approach trains RBMs one after another and uses their training data resulting for training stage in the next RBM using CD, PCD or FEPCD training methods. The last layer trains a joint density model with a discriminative RBM. We use the back-propagation technique through the whole classifier to fine-tune the weights in order to optimize the classification result. Table 3 illustrates the classification error before and after using back-propagation technique. We notice that the error decreases after using the back-propagation technique especially with FEPCD training. Figure 9 shows the best training performance that indicates the iterations at which the validation performance reached a minimum mean squared normalized error performance criterion. The best performance is obtained with FEPCD training.



(CD) *(PCD)* *(FEPCD)*

Figure 8: Best training performance on Washington RGBD dataset of 308-300-300-1500 GDBN structure. The minimum mean squared normalized error 0.013379 is reached at epoch 200 with FEPCD.



(CD) *(PCD)* *(FEPCD)*

Figure 9: Best training performance on Washington RGBD dataset of 308-300-300-1500 DDBN structure. The minimum mean squared normalized error 0.0052535 is reached at epoch 200 with FEPCD.

Table 3: Classification errors and accuracy on Washington RGBD dataset for 308-300-300-1500 DDBN structure using different training methods: CD, PCD and FEPCD. After training each RBM, DDBN is fine-tuned in 200 epochs using the back-propagation method.

	Before	**After**	**Acc.**
DDBN-CD	0.3810	0.3155	68.45%
DDBN-PCD	0.4491	0.0201	97.98%
DDBN-FEPCD	0.4053	**0.0111**	**98.89%**

6.3 Comparison to Other Methods

In this subsection, we compare our approach to related state-of-the-art approaches. Table 4 shows the main accuracy values and compares our 3D recognition pipeline to the published results (Lai et al., 2011a; Bo et al., 2011; Schwarz et al., 2015). Lai *et al.* (Lai et al., 2011a) extract a set of features that captures the shape of the object view using spin images, and another set which captures the visual appearance using SIFT descriptors. These features are extracted separately from both depth and RGB images. In contrast, we extract the geometric features from a single point cloud using only the VFH descriptor. A recent work by Schwarz *et al.* (Schwarz et al., 2015) uses both colorizing depth and RGB images that are processed independently by a convolutional neural network. CNN features are then learned using SVM classifier in order to successively determine the category, instance, and pose. In our approach, we use VFH features for training GDBN/DDBN with three hidden layers that model a deep network architecture. The results show also that our recognition pipeline with DDBN archtecture and FEPCD training works perfectly with the accuracy rate of 98.89% and outperforms all methods that are mentioned in the state-of-the-art.

Table 4: The accuracy rates on Washington RGBD dataset for 308-300-300-1500 DDBN structure using CD,PCD and FEPCD training methods that are compared with the state-of-the-art methods.

Methods	**Accuracy rates**
CNN (Schwarz et al., 2015)	89.4%
RGBD dataset (Lai et al., 2011a)	64.7%
Depth Kernel (Bo et al., 2011)	78.8%
DDBN-CD	68.45%
DDBN-PCD	97.98%
DDBN-FEPCD	**98.89%**

In general, the use of PCD training is better than CD training, and FEPCD outperforms PCD training. This result is pertinent, since FEPCD uses free energy as a criterion for the goodness of a chain in order to obtain elite samples from the generative model that can more accurately compute the gradient of the log probability of training data. FEPCD outperforms PCD and CD in terms of accuracy, although its computational complexity is high and takes relatively longer time in training as compared to the two methods. Our next goal will be to optimize the performance of FEPCD in order to reduce the computational complexity.

7 CONCLUSIONS

In this work, we focused on 3D object categorization using geometric features extracted from Viewpoint Feature Histogram (VFH) descriptor and learned with both Generative and Discriminative Deep Belief Network (GDBN/DDBN) architectures. GDBN is the probabilistic model with many Restricted Boltzmann Machines (RBMs) which are trained sequentially. On the other hand, DDBN is constructed from the Discriminative Restricted Boltzmann Machine (DRBM) which is based on RBM and the joint distribution model. The experimental results using DDBN are encouraging, especially that our approach is able to recognize 3D objects under different views. In a future work, we will attempt to embed our algorithm in our robot TurtleBot2 in order to grasp the real-world objects. Moreover, we will utilize a hybrid deep architecture that combines the advantage of generative and discriminative models.

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