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Two Hidden Layer Multiconnected Boltzmann Machine for Controlling Moving Objects

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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Abstract

There are various areas of industry where the remote control of machines significantly increases productivity. In terms of household this is extremely important for elderly and disabled people. Voice instructions are the most natural way of communication between employees from different hierarchical structures. The development of contemporary hardware allowing such relationships to build span between man and machine. Contact with the managed object of spoken language makes control very efficiently. Moving objects can be successfully controlled by voice commands having in mind that the voice control assures hands free and fast communication between human and controlled object. The present paper deals with the remote control of moving objects. Voice control is used for managing robots, drones, wheelchairs etc. A new stochastic classifier has been obtained for this purpose. A successful classification by a new two hidden layer Boltzmann machine has been realized. The process of deep machine learning has been studied with respect to the mean field approximation problem. An improved fixed-point iteration algorithm is used to accelerate the rate of convergence. An algorithm for training the classifier has been written explicitly in pseudocode. Real life tests are discussed.

Keywords: Voice control; signal processing; deep Boltzmann machine; mean field approximation.

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NOMENCLATURES

$\bar{v}$	*2-valent cepstral coefficient tensor of all frames representing a fixed word*
$\underline{v}_i$	*Cepstral coefficient vector of a fixed frame*
v_l	*Cepstral coefficient*
$\bar{h}^{(j)}$	*2-valent binary tensor of hidden units*
$\underline{h}_i^{(j)}$	*Hidden unit (binary vector)*
$\underline{u}$	*Vector of binary labels*
P	*Distribution*
$\langle\cdot\rangle_P$	*Expectation over the distribution P*
p	*Likelihood*
$\boldsymbol{H}$	*3-valent binary tensor containing both hidden layers*
m	*Number of visible units (frames)*
s_k	*Number of units in the k-th hidden layer*
n	*Number of the words in the basis*
t	*Number of training pairs*
σ_i	*Standard deviation of the input unit $\underline{v}_i$*
$w_{ij}, \widetilde{w}_{ij}$	*Weight matrices*
$W, \widetilde{W}$	*4-valent real-valued weight tensors or corresponding rectangular block weight matrices*
$\underline{U}_{ij}^{(k)}$	*Weight vectors*
$(\bar{v}, \underline{u})$	*A training pair*
$\boldsymbol{V}$	*Set of training pairs*
$\bar{a}$	*Offsets*
$\bar{b}, \bar{c}^{(j)}, \underline{d}$	*Biases*
Θ	*Set of all biases, offsets and weights of the neural network*
sigm	*Logistic function*
Sigm	*Multivariate sigmoid*
$\mathcal{N}$	*Multivariate Gaussian*
λ	*Learning rate*
η	*Number of necessary iterations for satisfying the stop criterion*
ν	*Number of unknowns in the mean field approximation problem*
$\|\cdot\|$	*Euclidean norm of a matrix*

1 Introduction

The remote control is one of the most contemporary approaches to exert influence on moving objects. It has been successfully combined with voice commands in the last decade. There are a lot of applications of voice control in the real life, for examples controlling of robots [1], drones, wheelchairs [2], home appliances [3,4] etc. The number of home systems with voice control is growing continuously. Voice banking [5] will become a hit in the not too distant future. We should also mention navigating systems, voice identification systems and telecommunications. The major advantage of voice control systems is hands-free communication with managed objects. Contemporary voice control is related to the probabilistic theory of deep machine learning.

Every voice control system needs a speech recognition module. Generally speaking an automatic speech recognition tool consists of a voice activity detector well known as VAD filter, signal preprocessing techniques and classifier. There are plenty of classification methods. The wavelet method, the dynamic time warping and various neural networks have been successfully used for classification during the last decades. The efficiency of the speech recognition systems strongly depends on the choice of classifier.

The first paper on Deep Boltzmann Machine (DBM) was published by Salakhutdinov and Hinton [6]. Results for multilayer Boltzmann machines can be found in [6-10]. The term DBM was introduced for the very first time by Salakhutdinov and Hinton [6]. They obtained a DBM with two hidden and one visible layers of binary units. Montavon and Müller [8] consider a simplified DBM with binary visible and hidden units. The authors present the energy function of the DBM as a function of centered states. They conclude that the centering procedure essentially facilitates the training of DBM. The idea with the centering trick is extended by Wang et al. [11] for Gaussian-binary deep Boltzmann machines. Deep Boltzmann machines as a feed-forward hierarchy is presented by Montavon et al. [12]. Salakhutdinov and Larochelle [13] developed a three layer DBM introducing very effective inference procedure. Cho et al. [7] considered DBM with n hidden layers on the basis of the enhanced gradient and parallel tempering. Zhou et al. [14] developed a deep neural network on the basis of n stacked RBMs. A layer-by-layer pretraining phase is used by Salakhutdinov and Hinton [10] in their efficient learning procedure for deep Boltzmann machines. From applied point of view the DMB is of significal practical importance. A DBM is used by Suk et al. [15] to process multimodal information from magnetic resonance imaging and diagnosing Alzheimer's disease.

The main goal of the present paper is to improve the stochastic model of voice control system obtained by Ilarionov et al. [16] designing a new deep classifier. The two hidden layer multiconnected classification Boltzmann machine is a natural extension of the RBM investigated in [16].

Further, the paper is organized as follows. A principle flowchart of voice control of a moving object is described in Section 2. A new DBM is obtained in Section 3. Algorithmic aspects of the two hidden layer multiconnected Boltzmann machine is analyzed in the same section. Various numerical experiments are discussed in Section 4. Section 5 contains some concluding remarks.

2 Stochastic Approach for Controlling a Moving Object

A detail scheme of the voice control of a moving object is presented on Fig. 1. The user says a voice command. The signal preprocessing includes Herz to mel conversion of the input signal and feature extraction. So many unpredictable noises can be found in a real environment. That is why we need a Wiener filter for noise reduction. The voice activity detection filter indicates the voice part of the signal. Speech recognition systems are not working properly in the case when a back ground speaker talk simultaneously with the user who pronounce voice commands. The authors test various commercial systems without success in the case when background noise contains speech. The present model is also inappropriate in this case.

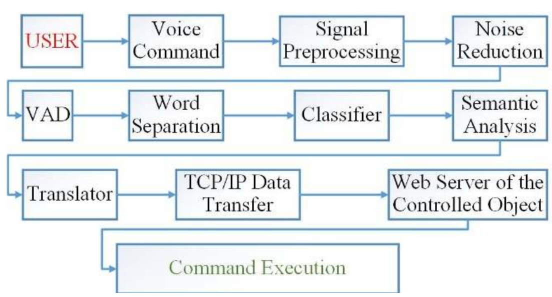

Fig. 1. Principal scheme of voice control of a moving object

The input command is separated into its constituent words. Each word is presented as a set of cepstral coefficient vectors (frames). The elements of all frames belong to $[0,1]$. The role of the classifier is to recognize the input command. The deep machine learning is related to this part of the signal processing. There are a lot of stochastic classifiers. We concentrate on a two hidden layer multiconnected Boltzmann machine. A semantic analysis is used to improve the recognition, for more details see [16]. After specifying the command, it is translated into the language of the moving object. Drones, robots and spy tanks are controlled by programming languages similar to BASIC. For instance EZ-Builder became very popular for managing robots. The translated command is sent to the web server of the controlled object. It follows an execution of the command.

3 Multiconnected Deep Boltzmann Machine

We assume that all hidden layers are connected excluding horizontal connections within a fixed layer. Boltzmann machines with horizontal connections within a fixed layer are said to be general Boltzmann machines as given by Salakhutdinov and Hinton [6]. The DBMs investigated in [6-8,11,13] are applied for image recognition. All considered models have a common feature. They only have connections between adjacent layers. We introduce a completely different approach. The proposed multiconnected deep Boltzmann machine has four layers, as shown in Fig. 2. The visible layer $\overline{v}$ consists of real-valued vectors of cepstral coefficients and it is connected with the top hidden layer $\overline{h}^{(1)}$. The hidden layers $\overline{h}^{(1)}$ and $\overline{h}^{(2)}$ consist of binary vectors and both layers are connected with each other. Additionally, we have a layer $\underline{u}$ with labels. The output layer $\underline{u}$ consists of binary units and it is connected with both hidden layers. Actually the proposed model is a natural generalization of the classification RBM obtained by Ilarionov et al. [16].

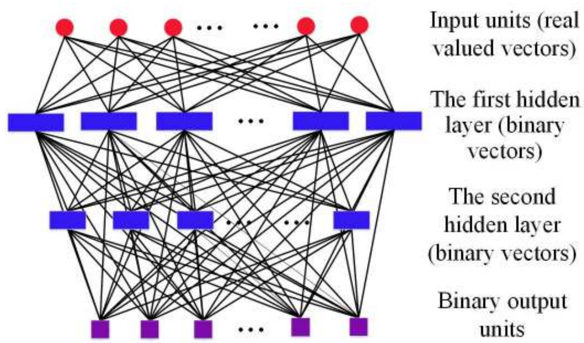

Fig. 2. The multiconnected deep Boltzmann machine

The energy of the model

$$E(\overline{v},\mathbf{H},\underline{u}) = \frac{1}{2}\sum_{i=1}^{m}\frac{\left(\underline{v}_i-\underline{a}_i\right)^2}{{\sigma_i}^2} - \sum_{i=1}^{m}\underline{b}_i\underline{v}_i - \sum_{j=1}^{2}\sum_{i=1}^{s_j}\underline{c}_i^{(j)}\underline{h}_i^{(j)} - \sum_{i=1}^{m}\sum_{j=1}^{S_1}\frac{\underline{v}_i^T w_{ij}\underline{h}_j^{(1)}}{\sigma_i}$$
$$- \sum_{i=1}^{S_1}\sum_{j=1}^{S_2}\left(\underline{h}_i^{(1)}\right)^T\widetilde{w}_{ij}\underline{h}_i^{(2)} - \sum_{i=1}^{n}d_i u_i - \sum_{k=1}^{2}\sum_{i=1}^{s_k}\sum_{j=1}^{n}\left(\underline{h}_i^{(k)}\right)^T\underline{U}_{ij}^{(k)}u_j$$

generates the following joint distributions:

$$P\left(\overline{v},\mathbf{H},\underline{u}\right) = \frac{e^{-E(\overline{v},\mathbf{H},\underline{u})}}{\sum_{\overline{v},\mathbb{H},\underline{u}}e^{-E(\overline{v},\mathbb{H},\underline{u})}},\ P\left(\overline{v},\underline{u}\right) = \frac{\sum_{\mathbb{H}}e^{-E(\overline{v},\mathbf{H},\underline{u})}}{\sum_{\overline{v},\mathbb{H},\underline{u}}e^{-E(\overline{v},\mathbf{H},\underline{u})}}.$$

Let

$$\mathbf{V} = \left\{\left(\overline{v}_i,\underline{u}_i\right)\middle| i = 1,2,\dots,t\right\},$$

be a set of training pairs. A supervised learning is applied in the present investigation. Each training word $\overline{v}_i$ is related to a binary label $\underline{u}_i$. Our purpose is to maximize the logarithmic likelihood,

$$L(\theta) = -\sum_{i=1}^{t}\log p\left(\overline{v}_i,\underline{u}_i\right),\ \theta\epsilon\Theta.$$

The contrastive divergence method for training Boltzmann machines attains significant popularity after Hinton [17] had been published way back in 2002. Most of the authors designing DBMs use the fixed-point iteration for deriving the mean field approximation [7]. This procedure is essentially improved by I. Goodfellow et al. [18].

We apply the contrastive divergence algorithm with mean field approximation to obtain the probability of each hidden neuron in all hidden layers to be active. Training the multiconnected DBM, we found the following difficulties: The mean-field fixed-point system of equations has not a solution for random initial guesses for the weight matrices, the fixed point iteration converges very slowly when the weight matrices are not normalized. We avoid these difficulties using normalized initial guesses for the weight matrices.

Our algorithm for training the two hidden layer multiconnected Boltzmann machine is presented in pseudo code to obtain a clear exposition of our idea. Before starting we center the offsets with respect to the training data. All elements of the visible layer belong to the interval [0,1] as it is done in by Ilarionov et al. [16]. The output units satisfy,

$$\sum_{i=1}^{n} u_i = 1.$$

Algorithm 1

% Contrastive divergence algorithm for training the
% classification multiconnected Boltzmann machine.
% --
% Initialization
create offsets
center offsets
% The initial approximations for all of the visible and % output units are set randomly.
create $\overline{h}_i^{[0]}$, $i = 1,2$ **randomly**
create $\underline{u}^{[0]}$, $\overline{v}^{[0]}$ **randomly**
create all elements of biases and offsets randomly in [0,1]
create normalized and positive definite weight matrices
create normalized weight vectors
% Positive phase
% --
forall $(\bar{v}, \underline{u}) \in \mathrm{V}$ **do**
% The index i shows the current number of the training pair.
begin
% The mean field approximation
% The value K indicates the number of iterations.
for $k = 0$ **to** $K - 1$ **do**
begin
% The first hidden layer
for $j = 1$ **to** s_1 **do**
% The index j shows the number of the current
% hidden unit in the first hidden layer.
begin
$\underline{h}_{1j}^{[k+1]} \coloneqq \mathrm{Sigm}\left(\underline{c}_j^{(1)} + \sum_{i=1}^{m} \frac{v_i^T w_{ij}}{\sigma_i} + \sum_{i=1}^{s_2} \widetilde{w}_{ij} \underline{h}_{2i}^{[k]} + \sum_{i=1}^{n} \underline{U}_{ji}^{(1)} u_i\right)$
end j

% The second hidden layer
for $j = 1$ **to** s_2 **do**
% The index j shows the number of the current
% hidden unit in the second hidden layer.

```
        begin
          $h_{2j}^{[k+1]} := \mathrm{Sigm}\left(\underline{c}_j^{(2)} + \sum_{i=1}^{s_1}\left(\underline{h}_{1i}^{[k+1]}\right)^T \widetilde{w}_{ij} + \sum_{i=1}^{n} \underline{U}_{ji}^{(2)} u_i\right)$
        end $j$
      end $k$
   end forall
% Approximate values for all units in each hidden layer
% are obtained by $K$ iterations.
$\widehat{\mathbb{H}} := \left(\overline{h}_1^{[k]}, \overline{h}_2^{[k]}\right)$;
% Negative phase
% ---------------------------------------------------
forall $(\bar{v}, \underline{u}) \in \mathrm{V}$ do
% The index $i$ indicates the current number of the training pair.
  begin
    % The positive phase results are used as initial guesses
    $\underline{u}^{[0]} := \underline{u}$;  $\overline{v}^{[0]} := \overline{v}$;
    for $k = 0$ to $K - 1$ do
      begin
        for $j = 1$ to $s_1$ do
        % The index $j$ shows the number of the current
        % hidden unit in the first hidden layer.
          begin
            $\underline{h}_{1j}^{[k+1]} \sim P\left(\underline{h}_{1j}^{[k]} \middle| \overline{v}^{[k]}, \overline{h}_2^{[k]}, \underline{u}^{[k]}\right)$
          end $j$
        for $j = 1$ to $s_2$ do
        % The index $j$ indicates the number of the current
        % hidden unit in the second hidden layer.
          begin
            $\underline{h}_{2j}^{[k+1]} \sim P\left(\underline{h}_{2j}^{[k]} \middle| \overline{h}_1^{[k+1]}, \underline{u}^{[k]}\right)$
          end $j$
        for $j = 1$ to $m$ do
        % The index $j$ shows the number of the current
        % visible unit.
          begin
            $\underline{v}_j^{[k+1]} \sim P\left(\underline{v}_j^{[k]} \middle| \overline{h}_1^{[k+1]}\right)$
          end $j$
        for $j = 1$ to $n$ do
        % The index $j$ indicates the number of the current
        % output unit.
          begin
            $u_j^{[k+1]} \sim P\left(u_j^{[k]} \middle| \mathbf{H}^{[k+1]}\right)$
          end $j$
      end $k$
end forall
% Approximate values for each unit of each hidden layer % are obtained by
means of $K$ iterations.
$\widetilde{\mathbb{H}} := \left(\overline{h}_1^{[k]}, \overline{h}_2^{[k]}\right)$;  $\tilde{v} := \overline{v}^{[k]}$;  $\tilde{u} := \underline{u}^{[k]}$;
% Update
```

```
% -------
for θ ∈ Θ do
  begin
     θ ≔ θ − λ(∂/∂θ E(v̄, ℍ̂, u̲) − ∂/∂θ E(ṽ, ℍ̃, ũ))
  end θ
end of Algorithm 1
```

For the negative phase we used the following conditional distributions:

$$P\left(\underline{v}_i \middle| \overline{h}^{(1)}\right) = \mathcal{N}\left(\underline{a}_i + \underline{b}_i + \sigma_i \sum_{j=1}^{s_1} w_{ij}\underline{h}_j^{(1)}, \sigma_i^2 I\right),$$

$$P\left(u_j \middle| \mathbf{H}\right) = \mathrm{sigm}\left(d_j + \sum_{k=1}^{2}\sum_{i=1}^{s_k} \underline{h}_i^{(k)} \underline{U}_{ij}^{(k)}\right),$$

$$P\left(\underline{h}_j^{(1)} \middle| \overline{v}, \overline{h}^{(2)}, \underline{u}\right) = \mathrm{Sigm}\left(\underline{c}_j^{(1)} + \sum_{i=1}^{m} \frac{\underline{v}_i^T w_{ij}}{\sigma_i} + \sum_{i=1}^{s_2} \widetilde{w}_{ij}\underline{h}_i^{(2)} + \sum_{i=1}^{n} \underline{U}_{ji}^{(1)} u_i\right),$$

$$P\left(\underline{h}_j^{(2)} \middle| \overline{h}^{(1)}, \underline{u}\right) = \mathrm{Sigm}\left(\underline{c}_j^{(2)} + \sum_{i=1}^{s_1} \left(\underline{h}_i^{(1)}\right)^T \widetilde{w}_{ij} + \sum_{i=1}^{n} \underline{U}_{ji}^{(2)} u_i\right).$$

We essentially improve the rate of convergence of the fixed-point iterations applying a new block iteration method of Gauss-Seidel type as in the positive and in the negative phase, see Algorithm 1. Similar approach is used by Gutiérrez et al. [19] solving nonlinear equations in the complex plane. Applying the new method we use,

$$u_j^{[k+1]} \sim P\left(u_j^{[k]} \middle| \mathbf{H}^{[\boldsymbol{k}+\mathbf{1}]}\right)$$

instead of

$$u_j^{[k+1]} \sim P\left(u_j^{[k]} \middle| \mathbf{H}^{[\boldsymbol{k}]}\right)$$

for instance. To classify an unlabeled input v̲, we solve the problem.

$$k = \underset{i=1,2,\dots,n}{\mathrm{argmax}}\, p(\overline{\boldsymbol{v}}, u_i)$$

Then the input $\overline{\boldsymbol{v}}$ is recognized as the word $\overline{\boldsymbol{v}}_{\boldsymbol{\kappa}}$, if $p(\overline{\boldsymbol{v}}, \mathrm{u}_k) > \frac{1}{2}$.

If $p(\overline{\boldsymbol{v}}, \mathrm{u}_k) \le \frac{1}{2}$ we conclude that the input $\overline{\boldsymbol{v}}$ has not a corresponding word in the data base. Successfully recognized data are stored for additional training of the DBM. Additionally we use a semantic analysis to improve the quality of recognition as it is done by Ilarionov et al. [16].

4 Numerical Tests

In designing a neural network, we apply deep machine learning. This process is realized on the basis of the mean field approximation problem in [7,9,20-22]. The role of the mean field approximation is to establish which neurons in the hidden layers are active. Development of sufficient conditions for existence and uniqueness of the exact solution of the mean field approximation problem is a crucial point designing

DBMs. Numerical tests indicate that there is a class of problems without solutions. A rigorous proof of this phenomenon could be made but it is beyond our consideration. The lack of solution leads to improper working of the corresponding neural network. Any divergent mean field approximation procedure generates confusions in the process of deep machine learning. The best way to avoid this difficulty is to work with normalized weight matrices. Note that there is a higher rate of convergence with a smaller norms of the weight matrices. Usually the initial guesses for the hidden units are chosen randomly. This is a tradition designing neural networks. That is why it is very important to establish convergence in the case of random initial guesses. This is another difficulty training a DBM. Moreover a monotone decreasing of the error norm is strongly desirable. On the other hand it is very important to obtain fast convergence of the approximate solutions and the number of necessary iterations to satisfy the stop criterion should be independent of the number of unknowns. The training of the DBMs depends on the norms of the weight matrices. All authors in [7,9,20-22] use the method of successive approximations to realize the fixed-point iteration. We extended the 4-valent weight tensors W and $\widetilde{W}$ to square block matrices adding zero blocks where it is necessary. The obtained block weight matrices are written by the same letters. If W and $\widetilde{W}$ are normalized the number of necessary iterations η for satisfying the stop criterion is independent of the number of unknowns, Fig. 3. We established low rate of convergence in the cases when the norms of the weight matrices is bigger than four. In this case not only that the number η is not proportional to the number of unknowns, but it grows unlimitedly when ν tends to infinity, see Fig. 4. The inequalities $4 < \|W\| \ll \|\widetilde{W}\|$ and $4 < \|\widetilde{W}\| \ll \|W\|$ generate much worse results. Comparing the method of successive approximations, Figs. 3 and 4, and the block iteration method proposed by the authors Figs. 5 and 6, we establish that the new method essentially reduces the number of necessary iterations for satisfying the stop criterion. The block iteration method remains stable even in the case when $\|W\| = \|\widetilde{W}\| = 7$, Fig. 5. The parameter η directly affects on the necessary time for training the DBM. Additionally, we found a lot of cases when the method of successive approximations is divergent especially in the case of ill-conditioned weight matrices.

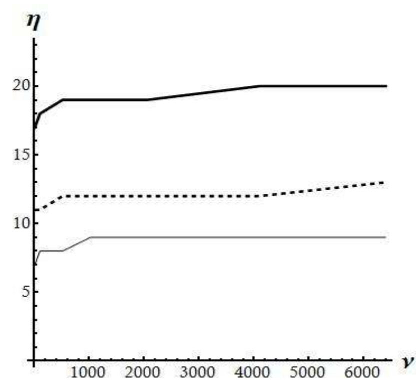

Fig. 3. The method of successive approximations. Relations between the number of unknowns and the number of necessary iterations for satisfying the stop criterion. The following legend is used: Thin line $\|W\| = \|\widetilde{W}\| = 1$, dashed line $\|W\| = \|\widetilde{W}\| = 2$, thick line $\|W\| = \|\widetilde{W}\| = 3.98$.

Let us denote the model for controlling moving objects obtained in the present paper by M_2 and the model obtained by Ilarionov et al. in [16] by M_1. We compare both models on the same experimental data base. It was proved in [16] that the success of recognition strongly depends on the number of hidden units. Moreover, an optimal number of hidden units in regard to the classification success was obtained. For the model M_1, this number varies between 200 and 250. To obtain the same result with the model M_2, we need approximately 70 hidden units located in two layers. The latter means that there is a serious reduction of the number of hidden units. The time for training the DBM depends on the norm of the weight matrices W and $\widetilde{W}$, see Figs. 3-6. We do not use random initial guesses for the weight matrices. All computational tests are made by positive definite and normalized initial guesses for W and $\widetilde{W}$. In this case, the model M_2 is much more reliable than M_1.

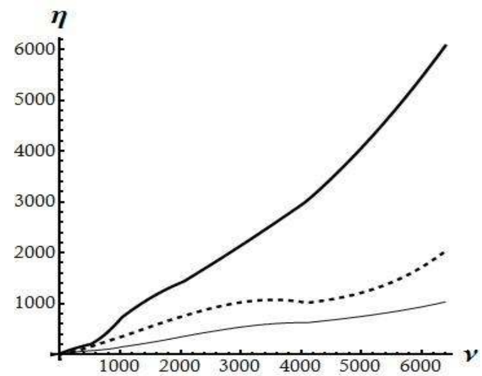

Fig. 4. The method of successive approximations. Relations between the number of unknowns and the number of necessary iterations for satisfying the stop criterion. The following legend is used: thin line $\|W\| = \|\widetilde{W}\| = 7$, dashed line $\|W\| = \|\widetilde{W}\| = 13$, thick line $\|W\| = \|\widetilde{W}\| = 19$

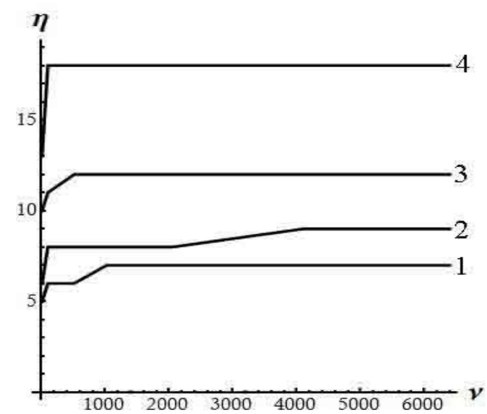

Fig. 5. The block iteration method proposed by the authors. Relations between the number of unknowns and the number of necessary iterations for satisfying the stop criterion. Denotations: 1. $\|W\| = \|\widetilde{W}\| = 1$, 2. $\|W\| = \|\widetilde{W}\| = 2$, 3. $\|W\| = \|\widetilde{W}\| = 3.98$, 4. $\|W\| = \|\widetilde{W}\| = 7$

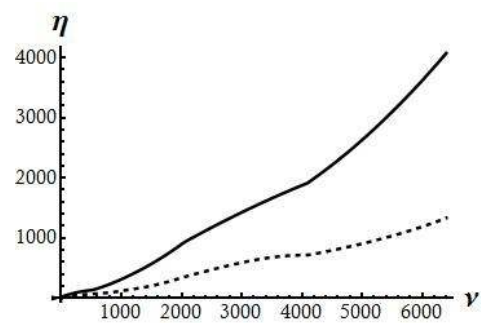

Fig. 6. The block iteration method proposed by the authors. Relations between the number of unknowns and the number of necessary iterations for satisfying the stop criterion Denotations: dashed line $\|W\| = \|\widetilde{W}\| = 13$, solid line $\|W\| = \|\widetilde{W}\| = 19$

5 Conclusion

A stochastic model with original classifier for controlling moving objects is investigated. A new DBM for classifying speech commands is obtained. A detailed algorithm for training the two hidden layer multiconnected Boltzmann machine has been presented. The present stochastic model is compared with the corresponding shallow version obtained by Ilarionov et al. [16] with respect to the experimental voice command data base. The implementation indicates that important restrictions on the weight matrices are necessary. A random choice of the initial guesses for the weight matrices could adversely affect the process of convergence of the mean field approximations. The best way is to work with positive definite and normalized weight matrices. In this case the present model is more reliable than the corresponding model with shallow classifier and it needs less number of hidden units. Some computational tests with ill-conditioned weight matrices failed since the mean field approximation algorithm is divergent. Smaller norms of the weight matrix generates higher rate of convergence. All authors designing DBMs applied the method of successive approximations to establish the state of neurons in hidden layers to be active. It is well-known that the method generates low rate of convergence especially in the case when the norm of the Jacobian of the system is close to one. The iterative method of Gauss-Seidel type proposed by the authors essentially reduce the number of necessary iterations for satisfying the stop criterion. The idea is attractive because it is easy for implementation. The necessary time for training a DBM can be decreased more if the mean field approximation problem is solved by methods with higher rate of convergence.

Competing Interests

Authors have declared that no competing interests exist.

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