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# Orthogonal Margin Maximization Projection for Gait Recognition

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**Abstract.** An efficient supervised orthogonal nonlinear dimensionality reduction algorithm, namely orthogonal margin maximization projection (OMMP), is presented for gait recognition in this paper. Taking the local neighborhood geometry structure and class information into account, the proposed algorithm aims to find a projecting matrix by maximizing the local neighborhood margin between the different classes and preserving the local geometry structure of the data. After projecting, the data points in the same class are pulled as close as possible, while the data points in different classes are pushed as far as possible. The highlights of OMMP include (1) takes both of the local information and class information of the data into account; (2) considers the effect of the noisy points and outliers; (3) it is supervised and orthogonal; and (4) its physical meaning is very clear. The experimental results on a public gait database show the effectiveness of the proposed method.

**Key words:** biometric, gait recognition, nonlinear dimensionality reduction, orthogonal margin maximization projection (OMMP).

## 1. Introduction

Biometric systems for automated personal identification and verification have received extensive attention in the last years. These systems utilize distinct behavioral or physiological characteristics in order to determine or verify the identity of an individual (Ramirez-Cortes *et al.*, 2011; Ribaric *et al.*, 2008). The biometric characters include fingerprint, iris, palmprint, face, gait, vice, handwriting, etc. Fingerprint, iris, palmprint and face recognitions are regarded as four reliable and accurate biometric identification technologies, but they often require user's cooperation. Face and vice recognition suffer from the disguise. So those methods are not suitable for important public areas where surveillance of security needs to be done at a distance. Gait recognition, as a newly emerging biometric identification, is used to identify individuals by the image sequences of their walking (BenAbdelkader *et al.*, 2004; Delac and Grgic, 2004), which has attracted growing attention because of its great potential uses to identify humans at a distance. Different from

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fingerprint, iris and face, gait has many unique advantages, such as remoteness, lower requirement of video quality and difficulty to disguise. Gait recognition is a challenging task in realistic surveillance scenarios in which people walking along arbitrary directions are viewed by a single camera. The earliest work on human motion perception was performed by Johansson (1973). He used moving light display fixed on the subjects to produce gait image sequences, and proved that people can identify others according to the perceptive motion type. So far, many gait recognition algorithms have been proposed. Lee and Grimson (2002) divided the walking silhouette into seven regions to extract both the gait average appearance feature vector and the gait spectral component feature vector for human recognition. BenAbdelkader *et al.* (2002) applied principal component analysis (PCA) to classify an unknown person with the computed self-similarity plot. Lam and Lee (2006) proposed a gait recognition algorithm that fuses motion and static spatio-temporal templates. Wang *et al.* (2003) converted 2D silhouette sequence to 1D data that is composed of distances to shape centroid and classified the walkers after having reduced the dimensionality of the feature by PCA. Hong *et al.* (2007)proposed a gait recognition method by the sequences of temporally ordered mass vector and used the dynamic time warping approach for matching measurement. Johnson and Bobick (2001) presented a gait recognition technique based on static body parameters recovered during the walking action across two different side-views in depth with a single camera. Huang and Boulgouris (2008) investigated the contribution of each view direction to the recognition performance using the CMU MoBo database. Kusakunniran *et al.* (2012) proposed a sparse regression-based view transformation model (VTM) for gait recognition under various views, in which regression processes are used to formulate and model the correlated motions among the gaits under different views. To achieve a reliable regression, the region of interesting (ROI) selection is a key process to filter source gait feature and remain with only relevant information to predict corresponding information in target gait feature. The refined ROI can be used to generate more stable and non-overfitting regression fitted model in VTM construction. Based on a 3-D linear model and Bayesian rule, Zhang and Troje (2005) introduced a view-independent person identification from human gait. The 3-D linear model is constructed using PCA from a set of Fourier represented examples. The coefficient sets are used as signature to describe the gait data, which are derived from projecting the 2-D gait sequences under the different views onto a 3-D model by means of a maximum of posterior estimate. Liu and Tan (2010) proposed a view invariant gait recognition method, which learns LDA-subspaces to extract discriminative information from gait features under each viewing angle in the training dataset. In testing phase, each gait feature is projected to the subspace separately. Then, final gait distance is a weighted sum of matching results from each subspace. However, the high-dimensional gait data often show the characteristics of non-linear, adaptive and multi-faceted nature. The traditional linear dimensionality reduction methods, such as PCA and LDA, can not deal with the nonlinear gait data processing problems and maintain the non-linear structure in gait data. In fact, many proposed gait recognition methods are effective under the ideal conditions and assume that only one person is in visual field. As we know, the physical environment of human walking is more complex than the assumptions. The goal of the research is to apply gait recognition to real condition. But all above gait recognition algorithms cannot meet the needs of the surveillance and security systems at a distance. So far, gait recognition technology is still in its developing stage, and has not been deployed in airports, border crossings and other important public access areas, since gait recognition rates are influenced by a lot of covariate factors, such as walking surface and speed change, wearing a coat, carrying bag, footwear and clothing, carrying conditions, lightning, viewpoint and time of execution, etc. In gait recognition, dimensionality reduction is a key step. Since the gait data are of high-dimensionality, nonlinear, complex and changing, the gait classifying features are not robust enough to the variations of the above factors, extracted by the existing image processing technology, statistic methods and linear dimensional reduction methods. In fact, the interaction between gait variables is a complex non-linear fashion because of the intrinsic non-linear dynamics of human movement. Recently, manifold learning, as a relatively advanced powerful tool for non-linear dimensionality reduction, has been successfully applied to pattern recognition such as face recognition (Roweis and Saul, 2008; Hui and Chen, 2007). Its basic idea is to discover the intrinsic structure of the data with low-dimensionality preserving geometric structure of the underlying manifold in the high dimensional data, based on the assumption that the data with significant feature resides in the neighborhood of a low-dimensional manifold. In actual gait recognition, one can regard the significant gait features as the low-dimensional manifold embedded in the high dimensional gait features space.

In this paper, we apply the manifold learning algorithm for the quantitative analysis of gait data to obtain the "true" nonlinear gait features from the high-dimensionality input space, thus providing a significant amount of information for gait classification. Average neighborhood margin maximization (ANMM) is an effective supervised nonlinear dimensionality reduction method (Wang and Zhang, 2007). For each data point, ANMM aims at pulling the neighboring points with the same class label towards it as close as possible, while simultaneously pushing the neighboring points with different labels away from it as far as possible. As for gait recognition, based on ANMM, we present a new robust nonlinear dimensionality reduction algorithm, named orthogonal margin maximization projection (OMMP). Similar to ANMM, OMMP also aims to learn a projection matrix such that the data in the low-dimensionality projected space have high within-class similarity and between-class separability. By the projection matrix, the original data can be conveniently transformed into a low-dimensional discriminant subspace in which it is more suitable for classification tasks. It can overcome the out-of-sample and small-sample-size (SSS) problem. The advantages of OMMP have been verified in the experiments on one public standard gait database, in which our method achieved a straight best recognition rates on both databases.

The rest of this paper is organized as follows: Section 2 describes the OMMP algorithm for the classification task. Experimental results on one public gait dataset are presented in Section 3. Finally, some concluding remarks and possible future research direction are provided in Section 4.

## 2. Orthogonal Margin Maximization Projection (OMMP)

Similar to other supervised manifold learning based methods, OMMP aims to find a linear projection matrix $A$, with which the data points are mapped into a low-dimensionality subspace where the nearby points with the same label are close to each other, while the nearby points with different labels are far apart.

Let $X = [x_1, x_2, \dots, x_n]$ be a set of $n$ data points in a $D$-dimensional space, i.e. $x_i \in R^D$, and assume that each data point belongs to one of $C$ classes $C_1, C_2, \dots, C_c$, then the dimensional reduction algorithm tries to find a corresponding output set of patterns $Y = [y_1, y_2, \dots, y_n]$ such that $y_i \in R^d$, $y_i = A^T x_i$, where $A$ is a linear projection matrix, $d \ll D$ and $Y$ provides the optimal representation of $X$ in the lower dimensional space. In the graph embedding framework, a graph regularly characterizes the local neighborhood relationships among the training data. Let $G = (X, W)$ be an undirected weighted graph with vertex set $X$. For each data point $x_i$, its $k$ nearest neighborhood set $N(x_i)$ can be split into two subsets, within-class neighbor $N_w(x_i)$ and between-class neighbor $N_b(x_i)$. The similarity matrix $W$ between $x_i$ and its $k$ nearest neighborhood $x_j$ is expressed as follows

$$y(x) = \begin{cases} \exp\left(\frac{-\|x_i - x_j\|^2}{\beta}\right), & x_j \in N(x_i) \text{ or } x_i \in N(x_j), \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where $\beta$ is a parameter, which is used as a regulator when the distance of $x_i$ and $x_j$ is larger.

From Eq. (1), it is obvious that among all the neighbors of $x_i$, the smaller between the point $x_j$ and $x_i$ is, the more similar it is to $x_i$. If there are noisy points or outliers in the neighborhood set, the similarity measure is not reliable. For example, the relative distance between the clean data point $x_i$ and the outlier $x_j$ is typically much larger than the other neighbors. Therefore, we define the reliability of $x_i$ as follows

$$R_i = \frac{D_{ii}}{\sum_i D_{ii}}, \tag{2}$$

where $D_{ii} = \sum_j W_{ij}$.

The larger $R_i$ of $x_i$ is, the more compact its neighborhood distribution is on the global manifold structure. This is to say, $x_i$ and its neighbors are much more similar to each other. On the contrary, if $R_i$ of $x_i$ is much smaller than the other points, $x_i$ is likely to be a noisy point or outlier. Hence, $R_i$ can be applied to the objective function to further reduce the influence of the noisy point and outliers on the projecting and preserve the global structure to some extent.

For classification task, based on ANMM, two optimal objective functions are defined as follows,

$$\max_A \sum_{i=1}^{n} \sum_{x_j \in N_b(x_i)} \frac{R_i}{\|N_b(x_i)\|} (y_i - y_j)^2, \tag{3}$$

$$\min_A \sum_{i=1}^{n} \sum_{x_j \in N_w(x_i)} \frac{R_i}{\|N_w(x_i)\|}(y_i - y_j)^2, \tag{4}$$

where $\| \ \|$ is the size of the set.

Eq. (3) aims at pushing the neighboring points with different labels away from it as far as possible, while Eq. (4) aims at pulling the neighboring points with the same class label towards it as close as possible. Combining Eqs. (3) and (4) to map the points in the within-class samples as close as possible and simultaneously map the points in the between-class samples as far as possible, we define an optimal objective function,

$$\max_A \left[ \sum_{i=1}^{n} \sum_{x_j \in N_b(x_i)} \frac{R_i}{\|N_b(x_i)\|}(y_i - y_j)^2 - \sum_{i=1}^{n} \sum_{x_j \in N_w(x_i)} \frac{R_i}{\|N_w(x_i)\|}(y_i - y_j)^2 \right]. \tag{5}$$

By simple algebra transforms, the first part and the second part of Eq. (5) are respectively reduced as

$$\begin{aligned}
&\sum_{i=1}^{n} \sum_{x_j \in N_b(x_i)} \frac{R_i}{\|N_b(x_i)\|}(y_i - y_j)^2 \\
&\quad = \sum_{i=1}^{n} \sum_{x_j \in N_b(x_i)} \frac{R_i}{\|N_b(x_i)\|}\left(A^T x_i - A^T x_j\right)^2 \\
&\quad = A^T \left[ \sum_{i=1}^{n} \sum_{x_j \in N_b(x_i)} \frac{R_i}{\|N_b(x_i)\|}(x_i - x_j)^2 \right] A \\
&\quad = \operatorname{tr}\left(A^T B A\right),
\end{aligned} \tag{6}$$

$$\begin{aligned}
&\sum_{i=1}^{n} \sum_{x_j \in N_w(x_i)} \frac{R_i}{\|N_w(x_i)\|}(y_i - y_j)^2 \\
&\quad = \sum_{i=1}^{n} \sum_{x_j \in N_w(x_i)} \frac{R_i}{\|N_w(x_i)\|}\left(A^T x_i - A^T x_j\right)^2 \\
&\quad = A^T \left[ \sum_{i=1}^{n} \sum_{x_j \in N_b(x_i)} \frac{R_i}{\|N_w(x_i)\|}(x_i - x_j)^2 \right] A \\
&\quad = \operatorname{tr}\left(A^T C A\right),
\end{aligned} \tag{7}$$

where $B = \sum_{i=1}^{n} \sum_{x_j \in N_b(x_i)} \frac{R_i}{\|N_b(x_i)\|}(x_i - x_j)^2$, $C = \sum_{i=1}^{n} \sum_{x_j \in N_w(x_i)} \frac{R_i}{\|N_w(x_i)\|}(x_i - x_j)^2$.

Then Eq. (5) is rewritten as

$$\max_A \operatorname{tr}\left[A^T (B - C) A\right]. \tag{8}$$

Using the Lagrangian method, it can be easily found that the optimal projection matrix $A$ is composed of $d$ eigenvectors $a_1, a_2, \dots, a_d$ corresponding to the largest $d$ eigenvalues of $B - C$.

To eliminate the freedom and weaken the noise, we add the orthogonal constraint to Eq. (8). There is a simple method to get the orthogonal projection matrix $P$ from the matrix $A$.

Set $p_1 = a_1$ and assume that $m - 1$ orthogonal basis vectors $p_1, p_2, \dots, p_{m-1}$ have been obtained. The $m$-th orthogonal vector $p_m$ can be computed by Eq. (9),

$$p_m = a_m - \sum_{i=1}^{m-1} \frac{p_i^T a_m}{p_i^T p_i} p_i. \tag{9}$$

From linear algebra, it is easy to know that the vectors $p_1, p_2, \dots, p_d$ are orthogonal to each other. Once $P = [p_1, p_2, \dots, p_d]$ has been learned, any new test point $x_new$ is mapped into the low-dimensionality subspace by

$$x_{new} \to y_{new} = P^T x_{new}, \tag{10}$$

where $P \in R^{n\times d}$, $x_{new} \in R^D$, $y_{new} \in R^d$, $d \ll D$.

In summary, the main procedure of the proposed algorithm for the classification task can be described as follows:

(1) Project the original data into the PCA subspace, and throw away the small principal components to overcome the small-sample-size (SSS) problem.
(2) For each point $x - i$, find the sets: $k$ nearest neighborhood set $N(x_i)$, within-class neighborhood set $N_b(x_i)$ and between-class neighborhood set $N_w(x_i)$.
(3) Compute the reliability of $x_i$ by Eq. (2).
(4) Compute $B$ and $C$ by Eqs. (6) and (7).
(5) Construct the generalized eigenvector problem Eq. (8) and compute the corresponding eigenvectors and eigenvalues.
(6) Orthogonalize the eigenvectors by Eq. (9) and obtain the orthogonal projecting matrix $P$.
(7) Project any new test point $x_{new}$ by Eq. (10) to low-dimensionality $y_{new}$.
(8) Use $K$ nearest neighbor (K-NN) classifier to decide the class labels of $y_{new}$.

## 3. Experimental Results

In this section, we conduct a set of experiments on a public gait sequences database CASIA-A (http://www.cbsr.ia.ac.cn) to verify the effectiveness of the proposed method, and compare it with three representative dimensional reduction methods PCA + RT (Ali *et al.*, 2011), manifold learning (ML) (Wu, 2012) and statistical shape analysis (SSA) (Wang *et al.*, 2003) and three representative dimensionality reduction methods, such as ANMM (Wang and Zhang, 2007), discriminant projection embedding (DPE) (Yan and

Zhang, 2008) and orthogonal discriminant projection (ODP) (Li *et al.*, 2009). ANMM, DPE and ODP are three recently proposed supervised manifold learning methods. The database CASIA-A (http://www.cbsr.ia.ac.cn/) consists of 20 different persons. All persons walk on a straight line under normal conditions. Every subject is captured in three different view angles i.e., frontally (90°), laterally (0°) and obliquely (45°), respectively (Roweis and Saul, 2008). Each person has 4 sequences per-view. The database thus includes a total of 240 (2043) sequences. The length of each collected sequence varies with the pace of the walker, but the average is about 90 frames (Wang and Zhang, 2007). The original gait images need to be preprocessed to segment, crop, align and resize the gait silhouettes before constructing templates and dimensionality reduction, because the closer the walking person gets to the camera, the bigger the gait silhouette image will be. Here, we assume that silhouettes have been extracted from original human walking sequences, and denote the binary gait silhouette by:

$$s(i,j)=\begin{cases}1, & \text{belongs to the foreground,}\\ 0, & \text{otherwise.}\end{cases}\tag{11}$$

The gait area center $(c_i, c_j)$ of each silhouette can be computed by

$$c_i=\frac{1}{N}\sum_{i,j} i.s(i,j),\qquad c_j=\frac{1}{N}\sum_{i,j} j.s(i,j),\tag{12}$$

where $N$ is the number of foreground pixels, given by $N=\sum s(i,j)$. We resize gait silhouettes so that all silhouettes have the same height, and then centralize each silhouette image according to the horizontal center. All the images in database are removed the outer parts of an image to improve framing, and are set to be the size of $80\times 40$, denoted $x_1, x-2, \ldots, x_n$. We use the function 'rgb2gray' of Matlab to transform the RGB gait images to gray images. The brightness of each gait image is normalized as $x_i=x_i/\|x_i\|$. After normalization, the mean pixel value for the full image set is $M=\sum_{i=1}^{n} x_i/n$. Then every image deducts the mean as follows: $x_1-M, x_2-M, \ldots, x_n-M$. Figure 1 shows representative gait silhouette image after processing.

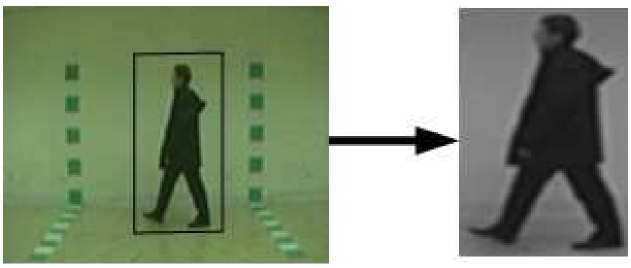

Fig. 1. Gait silhouette after preprocessing.

Finally, the gait data need to be transformed as vector by follows

$$X_i = \begin{bmatrix} x^i_{1,1} & \cdots & x^i_{1,64} \\ x^i_{2,1} & \cdots & x^i_{2,64} \\ \vdots & \ddots & \vdots \\ x^i_{64,1} & \cdots & x^i_{64,64} \end{bmatrix} \to \begin{bmatrix} x^i_{1,1} & \cdots & x^i_{1,64}, & \ldots, & x^i_{64,1} & \cdots & x^i_{64,64} \end{bmatrix}. \quad (13)$$

We use the function 'reshape' of Matlab to transform the gray images to vector images, expressed as $x_i$ $(i = 1, 2, \ldots, n)$. In each experiment, the image set from CASIA-A database is partitioned into the training set and test set. The training set is used to learn a gait subspace and obtain the projecting matrix. We randomly select half of gait images from each individual as training set and the rest as test set, and repeat the experiment 50 times under each condition. K-nearest-neighbor (KNN) classifier is employed for classification. Supposed the number of the training samples per class is known, denoted as $l$, the number of nearest neighbor $k$ can be set to $k = l - 1$. The justification for this choice is that each sample should connect with the remaining $l - 1$ samples of the same class.

When the distance of $x_i$ and $x_j$ is much larger, the value of $\exp(-\|x_i - x_j\|^2)$ may be very small or even negligible. The parameter $\beta$ aims to reduce the impact on the clustering ability of the reduction algorithm. But, $\beta$ is commonly acquired manually. Manually choosing $\beta$ is not only complex in computation, but also unstable. Li *et al.* (2009) concluded that the parameter $\beta$ shows its impact on the error rate when is small, when $\beta$ equals to or is larger than 300, the error rates almost keep unchanged. We set $\beta$ to be $\sqrt{\|X_i\|.\|X_j\|}$ (Zhang *et al.*, 2008).

In general, the gait recognition rates vary with the dimensionality of the gait subspace, so we record the highest recognition rate of each experiment. Table 1 shows the maximal average recognition rates across 50 runs of each method under simply K-NN classifier $(K = 1)$ and their corresponding standard deviations (std).

The results in Table 1 show that OMMP is superior to other methods and the reason is that OMMP considers not only the local neighborhood geometry structure and class labels, but also the reliability of the data and the orthogonal constraint. Therefore, OMMP is more effective for gait recognition.

Table 1
The recognition rate on CASIA-A database.

| Algorithms | Rec. rate at 0° | Rec. rate at 45° | Rec. rate at 90° |
|---|---|---|---|
| PCA + RT | $93.30 \pm 5.92$ | $92.37 \pm 4.27$ | $92.76 \pm 4.19$ |
| ML | $95.51 \pm 5.01$ | $94.56 \pm 4.27$ | $93.76 \pm 4.19$ |
| SSA | $95.84 \pm 5.10$ | $95.42 \pm 4.62$ | $94.95 \pm 4.78$ |
| ANMM | $96.80 \pm 5.53$ | $95.07 \pm 4.74$ | $94.43 \pm 4.20$ |
| DPE | $95.08 \pm 3.94$ | $95.52 \pm 4.25$ | $95.14 \pm 4.46$ |
| ODP | $95.52 \pm 3.88$ | $95.84 \pm 3.66$ | $94.48 \pm 4.60$ |
| OMMP | $98.03 \pm 5.93$ | $98.13 \pm 4.95$ | $97.52 \pm 5.08$ |

## 4. Conclusions

Gait recognition is an interesting biometric which does not undergo the limitations of other standard biometric methods such as iris or face recognition, as it can be applied at a distance to non-cooperative users. However, its potential practical use is heavily limited by the presence of multiple covariate factors which make identification problematic in actual scenarios. In this paper, we proposed an effective nonlinear dimensional reduction algorithm named OMMP for gait recognition, in which the local neighborhood geometry structure, class labels, the reliability of the data and the orthogonal constraint are considered. Experimental results have demonstrated the effectiveness of the proposed algorithm on CASIA-A database. There are two aspects that should be highlighted. Firstly, the reliability of each data point is defined and is introduced to the objective function. Secondly, the orthogonal projecting matrix is easily obtained by Gram-Schmidt orthogonalization method. Although we have achieved encouraging results on CASIA-A database, more experiments on some realistic gait databases are still required before the proposed method is applied to human identification system in real world environment. Natural extensions of the proposed methodology are the representation of gait sequences or cycles as 3D tensors instead of stacked vectors, and the application of second order of nonnegative tensor factorization to gait data, in order to make identity recognition robust to the covariate factors present. This will encourage more extensive adoption of gait identification with other classical biometrics. Further work is to validate the suitability of the proposed algorithm in actual application.

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## Ortogonalias paraštes maksimizuojanti projekcija eisenos atpažinimui

Shanwen ZHANG, Chuanlei ZHANG

Straipsnyje yra pristatomas netiesinis matmenų skaičiaus sumažinimo su mokytoju metodas – ortogonalias paraštes maksimizuojanti projekcija. Metodo pritaikymo demonstracijai pasirinktas biometrinis asmens atpažinimo iš eisenos uždavinys. Eksperimentams panaudota CASIA-A duomenų bazė, kurioje yra 20 žmonių video įrašai, nufilmuoti iš 3 skirtingų kampų.

Eisenos atpažinimo uždavinys dėl skirtingų sąlygų, tokių kaip apšvietimas, apranga, filmavimo kampas, yra sudėtingas, požymiai jautrūs sąlygoms ir daugiamačiai, o ryšiai tarp požymių netiesiniai. Su tikslu, išgauti kuo atsparesnius požymius, paprastai yra naudojamas matmenų skaičiaus sumažinimas. Autorių pasiūlytas matmenų skaičiaus sumažinimo algoritmas yra artimas vidutines kaimynystės paraštes maksimizuojančiai projekcijai, kuri stengiasi rasti tokią požymių transformaciją, kad suprojektuoti duomenys mažesnio matmenų skaičiaus erdvėje būtų kuo arčiau vienas kito, jei priklauso tai pačiai klasei, ir kuo toliau vienas nuo kito, jei yra iš skirtingų klasių. Klasę nagrinėjamo uždavinio atveju atitinka asmuo.

Esminės pasiūlytos projekcijos savybės: 1) išnaudojama lokali duomenų informacija apie kaimynus kartu su priklausymu klasei; 2) atspari triukšmui ir išskirtims duomenyse; 3) metodas yra mokymo su mokytoju tipo ir maksimizavime išnaudoja ortogonalumo apribojimą; 4) turi aiškią fizinę interpretaciją.