Matrix Neuro-Fuzzy Self-Organizing Clustering Network

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***Abstract* – In this article the problem of clustering massive data sets, which are represented in the matrix form, is considered. The article represents the 2-D self-organizing Kohonen map and its self-learning algorithms based on the winner-take-all (WTA) and winner-take-more (WTM) rules with Gaussian and Epanechnikov functions as the fuzzy membership functions, and without the winner. The fuzzy inference for processing data with overlapping classes in a neural network is introduced. It allows one to estimate membership levels for every sample to every class. This network is the generalization of a vector neuro- and neuro-fuzzy Kohonen network and allows for data processing as they are fed in the on-line mode.**

***Keywords* – Fuzzy clustering, matrix, self-organizing map**

I. Introduction

There are many control systems, processes and the signals, the flow of which is characterized by two-dimensional fields of measurements. Examples of such fields are electromagnetic, thermal and optical fields, areas of air pollution and surface water etc. An obvious example of such two-dimensional field is a digital TV image or a similar image to it, a set of brightness of luminescence elements, which forms a discrete two-dimensional field. As a rule, processing of such fields is made by a preliminary vectoring of their fragments and the subsequent analysis of a multidimensional (vector) process using traditional methods. In terms of computing this approach is ineffective. Therefore in some cases it is much more convenient to process a matrix signal directly and to do it without a vectoring and an opposite operation of vectoring (the devectoring operation). In addition, when an initial vector signal of high dimension is converted into in a more compact matrix form, the reverse situation is also possible.

It is necessary to notice that various problems of matrix signal processing, without the preliminary vectoring, have been attracting attention for a long time. Therefore, in [1, 2] problems of control of dynamic matrix objects (including adaptive) have been considered. In [3] the problem of a two-dimensional discrete filtration has been solved, and in [4, 5] – the identification and forecasting have been considered. In [6] the matrix algorithm for self-learning of a Kohonen map [7, 8] for processing (segmentation) of digital images has been proposed. In this article, the synthesis of an algorithm for self-learning of a neuro-fuzzy Kohonen map, which is intended for processing matrix signals (images) under conditions of overlapping classes, is proposed.

II. Neuro-Fuzzy Kohonen Map

Self-Organizing Maps (SOMs) were introduced by T.Kohonen [7]. Nowadays they are widely used for solving a wide class of Data Mining problems such as clustering, autoassociation, diagnostics, information compression, etc. The basic feature of Kohonen maps is their ability to self-learning without an external training signal ("a teacher") and the computational simplicity of implementation. These features have made SOMs popular among users of artificial neural networks. At the same time, the most popular rules of self-learning, based on principles «the winner takes all» (WTA) and «the winner takes more» (WTM), can appear inefficient under conditions of overlapping clusters when the same image with various levels of membership (probabilities, possibilities) can belong to several classes at once. That is why the synthesis of hybrid neuro-fuzzy systems, which integrate advantages of Kohonen maps and procedures of fuzzy clustering, is expedient [9].

Consequently, in [10, 11] the fuzzy Kohonen map (fuzzy SOM) has been introduced. Neurons of this network are replaced by fuzzy sets and fuzzy rules, which are set a priori by experts. Thus, the learning process is actually absent. In [12, 13] the fuzzy clustering map has been proposed. This neural network implements the classic clustering algorithm of fuzzy c-means (FCM) [14]. Like FCM, a fuzzy SOM processes data in a batch mode that does not allow using it in the on-line mode. In [15] the combined learning algorithm of a self-organizing map with a fuzzy inference has been proposed. This algorithm integrates the Kohonen and the Grossberg learning rules [16]. Unfortunately, the efficiency of this algorithm essentially depends on a well-founded choice of its free parameters. In [17-19] the recurrent algorithms of self-learning, which are hybrids of Kohonen WTM-rules and adaptive algorithms of fuzzy clustering, have been developed [20]. Thus, as the neighborhood function, the levels of membership functions have been used. These levels of membership functions are defined by the accepted value of fuzzyfier, which essentially affects the final results.

A standard single-layered 1-D self-organizing neural Kohonen network is considered in [8]. It consists of n inputs and m neurons in the Kohonen layer. The process of its tuning includes a competition, cooperation and actually a synaptic adaptation. We also suppose that the training set with a priori unknown classification $x(k) = (x_1(k), x_2(k), \ldots, x_n(k))^T$, where $k = 1,2,\ldots,N$ is the number of sample in the training set or an index of current discrete time, is defined. Every neuron is an adaptive linear associator and has n synaptic weights $w_j(k)=(w_{j1}(k),w_{j2}(k),\ldots,w_{jn}(k))^T$, $j=1,2,\ldots,m$. The output signal of each neuron can be represented as:

$$y_j(k)=w_j^T(k-1)x(k), \tag{1}$$

and a network signal in the large – $y(k)=(y_1(k),y_2(k),\ldots,y_m(k))^T$; the input and output signals are preliminary normalized:

$$\|x(k)\|=\|w_j(k-1)\|=1. \tag{2}$$

At a competition stage on each step we find the winner neuron $w_j(k-1)$ for each input vector $x(k)$ that is fed to the network (in the accepted metric, in this case Euclidian). The winner neuron is defined by the minimum value of distance:

$$D_j(x(k),w_j(k-1))=\|x(k)-w_j(k-1)\|, \tag{3}$$

$$\begin{aligned}D_j^2(x(k),w_j(k-1))&=\|x(k)-w_j(k-1)\|^2=\\&=2(1-y_j(k))=2(1-\cos(x(k),w_j(k-)))\end{aligned} \tag{4}$$

Consequently, if (2) is used, $0\le D_j^2(x(k),w_j(k-1))\le 4$, and $-1\le y_j(k)\le 1$.

If the cooperation stage is left out, the WTA-rule is as follows:

$$w_j(k)=\begin{cases}\dfrac{w_j(k-1)+\eta(k)(x(k)-w_j(k-1))}{\|w_j(k-1)+\eta(k)(x(k)-w_j(k-1))\|},\\ if\ w_j(k-1)\ is\ the\ winner,\\ w_j(k-1)-otherwise,\end{cases} \tag{5}$$

where $\eta(k)$ – a learning rate parameter for adjustment of speed, chosen according to the rules of stochastic approximation. If the cooperation stage is used in the self-learning process, then the neighborhood function $\varphi(j,l,k)$ is considered, for which $\varphi(j,l,k)=1$. If any of neurons $w_l(k-1)$ moves away from the winner $w_j(k-1)$, this function decreases, and the WTM-rule for all neurons in the network is as follows:

$$w_l(k)=\frac{w_l(k-1)+\eta(k)\varphi(j,l,k)(x(k)-w_l(k-1))}{\|w_l(k-1)+\eta(k)\varphi(j,l,k)(x(k)-w_l(k-1))\|}. \tag{6}$$

If $l=j$, (6) agrees with the first relation in (5). Usually the Gaussian or another bell-shaped function is used as the membership function.

For simplification of calculations it is possible to refuse a competition stage and to “connect” a neighborhood function not to the winner neuron $w_j(k-1)$, but to an input vector $x(k)$. For this purpose in [15] the simple construction of neighborhood function without a winner has been used:

$$\varphi(l,k)=\frac{1+y_l(k)}{2}. \tag{7}$$

This function is a type of radial basis activation functions of the raised cosine; and it has been introduced in [21]. Then if in formula (6) we take into consideration (7), (6) can be rewritten as

$$w_l(k)=\frac{w_l(k-1)+\eta(k)\dfrac{1+y_l(k)}{2}(x(k)-w_l(k-1))}{\left\|w_l(k-1)+\eta(k)\dfrac{1+y_l(k)}{2}(x(k)-w_l(k-1))\right\|}. \tag{8}$$

where a unique free parameter is the learning rate parameter $\eta(k)$. In [15], the procedure has been used for its adjustment

$$\eta(k)=r^{-1}(k),\ r(k)=\alpha r(k-1)+\|x(k)^2\|,\ 0\le\alpha\le 1, \tag{9}$$

$$\frac{1}{k}\le\eta(k)\le 1. \tag{10}$$

If $\alpha=1$, this procedure satisfies necessary conditions of stochastic approximation.

At the same time, in [22] it has been shown that convergence of the learning procedure (6) is provided not only by reduction of a learning rate, but also by the constant narrowing of receptive field of neighborhood function. That is rather inconvenient to implement for the function (7) [15]. In this case, the use of the square-law Epanechnikov function [23-25], which can be represented as (11), is more perspective:

$$\begin{aligned}\varphi(l,k)&=\max\left\{0,1-\frac{\|x(k)-w_l(k-1)\|^2}{\sigma^2(k)}\right\}=\\&=\max\left\{0,1-\frac{D_l^2(x(k),w_l(k-1))}{\sigma^2(k)}\right\},\end{aligned} \tag{11}$$

where $\sigma^2(k)$ – the width parameter of the receptive field. The narrowing of the receptive field can be provided using the procedure [22]

$$\sigma(k)=\sigma(0)\exp\left(-\frac{k}{\beta}\right),\quad \beta>0. \tag{12}$$

It is interesting to note that when $\sigma=2$, the function (11) coincides with (7), because

$$\frac{1+y_l(k)}{2}=1-\frac{D_l^2(x(t),w_l(k-1))}{4}. \tag{13}$$

Since a receptive layer (11) is a hypersphere of the radius σ , then learning rule (6) with an Epanechnikov function (11) is a generalization of an images compression algorithm [26] with the membership function

$$\varphi(l,k)=\begin{cases}1,\quad \forall w_l(k-1),\ if\ \|x(k)-w_l(k-1)\|^2\le\sigma^2,\\ 0,\quad otherwise.\end{cases} \tag{14}$$

The self-organizing map, which is tuned by using a learning set $x(1),x(2),\ldots,x(N)$, can be employed for the classification (or clustering) of entering new samples $x(p),\ p=N+1,N+2,\ldots$. At the same time, if it is supposed a priori that clusters are overlapping, then it is necessary to evaluate the level of belonging of $x(p)$ to each generated cluster. To calculate this level, the modification of a standard FCM-estimate is used [9, 14]:

$$u_j(x(p)) = \frac{\|x(p)-w_j(N)\|^{-2} h(y_j(p))}{\sum_{l=1}^{m}\|x(p)-w_l(N)\|^{-2} h(y_l(p))}, \quad (15)$$

where $u_j(x(p))$ is the membership level of observation $x(k)$ to j cluster,

$$h(y_j(p)) = \begin{cases} 1, & if\ y_j(p) > 0, \\ 0, & otherwise. \end{cases} \quad (16)$$

$$y_j(p) = w_j^T(N)x(p). \quad (17)$$

It is obvious that all patterns for which

$$-1 \le \cos(x(p), w_j(N)) \le 0 \quad (18)$$

cannot belong to j cluster.

III. Self-Learning Matrix Algorithm

The section considers a one-layered 2-D self-organizing map that contains $(n_1 \times n_2)$ receptors on the input and $(m_1 \times m_2)$ neurons in the Kohonen layer.

The training set is represented as a sequence of matrix patterns $X(k) = \{x_{i_1 i_2}(k)\}$, $i_1 = 1,2,\ldots,n_1$; $i_2 = 1,2,\ldots,n_2$; $k = 1,2,\ldots,N$, each neuron is a matrix adaptive linear associator and has $(n_1 \times n_2)$ synaptic weights $W_{j_1 j_2}(k) = \{w_{j_1 j_2 i_1 i_2}(k)\}$, $j_1 = 1,2,\ldots,m_1$; $j_2 = 1,2,\ldots,m_2$. The output signal of neuron can be represented as

$$Y(k) = \{y_{j_1 j_2}(k)\},\ \ y_{j_1 j_2}(k) = Tr\, W_{j_1 j_2}^T(k-1)X(k), \quad (19)$$

at the same time, inputs are preliminary normalized so that

$$Tr\ X(k)X^T(k) = 1. \quad (20)$$

At a competition stage, on each step the winner neuron $W_{j_1 j_2}(k)$, which is the closest to the input vector $X(k)$, is defined in the matrix spherical norm

$$\begin{aligned} &D_{j_1 j_2}(X(k), W_{j_1 j_2}(k-1)) = \\ &= (Tr(X(k) - W_{j_1 j_2}(k-1))(X(k) - W_{j_1 j_2}(k-1))^T)^{\frac{1}{2}} \end{aligned} \quad (21)$$

$$D^2_{j_1 j_2}(X(k), W_{j_1 j_2}(k-1)) = 2(1 - y_{j_1 j_2}(k)). \quad (22)$$

In this case, WTA learning rule is the modification of the algorithm introduced in [6] and can be written as

$$W_{j_1 j_2}(k) = \begin{cases} (W_{j_1 j_2}(k-1) + \eta(k)(X(k) - W_{j_1 j_2}(k-1)))\times \\ (Tr(W_{j_1 j_2}(k-1) + \eta(k)(X(k) - W_{j_1 j_2}(k-1)))\times \\ (W_{j_1 j_2}(k-1) + \eta(k)(X(k) - W_{j_1 j_2}(k-1)))^T)^{-\frac{1}{2}}, \\ if\ W_{j_1 j_2}(k-1)\ is\ a\ winner, \\ W_{j_1 j_2}(k-1), \quad otherwise. \end{cases} \quad (23)$$

If in a self-learning process a competition stage is used, the scalar membership function is taken into consideration, for example, Gaussian with matrix argument

$$\phi(j_1 j_2, l_1 l_2, k) = \exp\begin{pmatrix} -\frac{1}{2} Tr(W_{j_1 j_2}(k-1) - W_{l_1 l_2}(k-1))\times \\ (W_{j_1 j_2}(k-1) - W_{l_1 l_2}(k-1))^T \sigma^{-2}(k) \end{pmatrix} \quad (24)$$

also a WTM learning rule for all neurons $m_1 m_2$ of a network is applied:

$$\begin{aligned} &W_{l_1 l_2}(k) = W_{l_1 l_2}(k-1) + \eta(k)\phi(j_1 j_2, l_1 l_2, k)(X(k) - W_{l_1 l_2}(k-1))\times \\ &\times(Tr(W_{l_1 l_2}(k-1) + \eta(k)\phi(j_1 j_2, l_1 l_2, k)(X(k) - W_{l_1 l_2}(k-1)))\times \\ &\times(W_{l_1 l_2}(k-1) + \eta(k)\phi(j_1 j_2, l_1 l_2, k)(X(k) - W_{l_1 l_2}(k-1)))^T)^{-\frac{1}{2}} \end{aligned} \quad (25)$$

the learning rate parameter is specified according to a recurrent relation:

$$\eta(k) = r^{-1}(k),$$

$$r(k) = \alpha\, r(k-1) + Tr\ X(k)X^T(k) = \alpha\, r(k-1) + 1. \quad (26)$$

In a self-learning mode without the winner, similarly to (7), the neighborhood function

$$\varphi(l_1 l_2, k) = \frac{1 + y_{l_1 l_2}(k)}{2} \quad (27)$$

and a self-learning rule

$$\begin{aligned} &W_{l_1 l_2}(k) = W_{l_1 l_2}(k-1) + \eta(k)\frac{1 + y_{l_1 l_2}(k)}{2}(X(k) - W_{l_1 l_2}(k-1))\times \\ &\times(Tr(W_{l_1 l_2}(k-1) + \eta(k)\frac{1 + y_{l_1 l_2}(k)}{2}(X(k) - W_{l_1 l_2}(k-1)))\times \\ &\times(W_{l_1 l_2}(k-1) + \eta(k)\frac{1 + y_{l_1 l_2}(k)}{2}(X(k) - W_{l_1 l_2}(k-1)))^T)^{-\frac{1}{2}}. \end{aligned} \quad (28)$$

are entered.

Further, we can introduce the matrix modification of Epanechnikov function (it is similar to (11)):

$$\begin{aligned} &\phi(l_1 l_2, k) = \\ &= \max\left\{0, 1 - \frac{Tr(X(k) - W_{l_1 l_2}(k-1))(X(k) - W_{l_1 l_2}(k-1))^T}{\sigma^2(k)}\right\} = \\ &= \max\left\{0, 1 - \frac{D^2_{l_1 l_2}(X(k), W_{l_1 l_2}(k-1))}{\sigma^2(k)}\right\} \end{aligned} \quad (29)$$

and to use it as a neighborhood function in the WTM-rule (28) instead of (27).

Finally we can use (30) instead of (15) to estimate a membership level of the pattern $X(p)$ in classes generated on a stage of synaptic adaptation.

$$\begin{aligned} &u_{j_1 j_2}(p) = (Tr(X(p) - W_{j_1 j_2}(N))(X(p) - W_{j_1 j_2}(N))^T)^{-1}\times \\ &\times h(u_{j_1 j_2}(p))\times \\ &\times(\sum_{l_1=1}^{m_1}\sum_{l_2=1}^{m_2}(Tr(X(p) - W_{j_1 j_2}(N))(X(p) - W_{j_1 j_2}(N)))^{-1} h(u_{j_1 j_2}(p)))^{-1}, \end{aligned} \quad (30)$$

where

$$h(y_{l_1 l_2}(p)) = \begin{cases} 1, & if \ y_{l_1 l_2}(p) > 0, \\ 0, & otherwise. \end{cases} \quad (31)$$

IV. CONCLUSIONS

A group of self-learning algorithms for the 2-D self-organizing neuro-fuzzy Kohonen map is proposed. These algorithms process not traditional vector signals, but patterns in the matrix form. It provides a number of computing conveniences in the analysis of the two-dimensional fields and high-dimensional data. The algorithms introduced in this paper are attractive thanks to their computational simplicity; they enable solving clustering problems under conditions of overlapping classes, which is important for solving a large class of real practical problems.

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Jevgenijs Bodjanskis, Valentina Volkova, Marks Skuratovs. Matricveida neiro-izplūdušais pašorganizējošais klasterizācijas tīkls
Apskatīts datu masīvu, kas doti matricas formā, klasterizācijas uzdevums. Tāpat tiek pieņemts, ka apstrādei paredzētie dati tiek papildināti secīgi tiešsaistes režīmā, bet paši klasteri, kurus veido šie dati, kādā veidā pārklājas tā, ka katrs ar matricu attēlotais tēls ar dažādiem piederības līmeņiem var vienlaicīgi piederēt uzreiz vairākām klasēm. Uzdevuma atrisināšanai ir ieviestas divdimensionāla T. Kohonena pašorganizējošā karte un tās apmācības algoritma modifikācija, balstoties uz likumiem „uzvarētājs iegūst visu" (WTA), „uzvarētājs iegūst vairāk" (WTM) un bez uzvarētāja. Ja pašapmācības procesā izmanto konkurences etapu, tad katrā solī tiek noteikts neirons uzvarētājs, kas matricas sfēriskajā metrikā ir vistuvākais izmantotajam ieejas tēlam, un tiek izmantota uz WTA likuma balstīta apmācība. Savukārt, ja pašapmācības procesā tiek izmantots kooperācijas etaps, tad tiek ieviesta skalāra kaimiņa funkcija, piemēram, Gausa funkcija ar matricas argumentu, un tiek pielietota uz WTM likuma balstīta apmācība visiem tīkla neironiem. WTM apmācības procedūras konverģence visiem tīkla neironiem tiek nodrošināta, samazinot meklēšanas soli un pastāvīgi sašaurinot kaimiņu funkcijas receptoro lauku, kas sarežģī apmācības procesa realizāciju tāda veida funkcijai. Tāpēc par kaimiņu funkciju tradicionālo Gausa funkciju vietā ir piedāvāts izmantot V. Epanečnikova funkcijas. Tāpat darbā piedāvāta divdimensionāla neiro-izplūdušās Kohonena kartes modifikācija un tās apmācības adaptīvais algoritms, kas ļauj novērtēt gan klasteru prototipu (centroīdu) parametrus, gan piederības līmeņus. Ir parādīts, ka apmācības algoritms ir izplūdušās c-vidējo metodes modifikācija. Piedāvātais matricu algoritms, atsakoties no vektorizācijas un devektorizācijas operācijām, nodrošina daudzas priekšrocības skaitliskajā realizācijā pār tradicionālajām pieejām, kad tiek apstrādāti divdimensionāli lauki un liela izmēra datu masīvi.

Евгений Бодянский, Валентина Волкова, Марк Скуратов. Матричная нейро-нечёткая самоорганизующаяся кластеризирующая сеть
Рассмотрена задача кластеризации массивов данных, заданных в матричной форме. При этом предполагается, что данные поступают на обработку последовательно в *on-line* режиме, а сами кластеры, образуемые этими данными, некоторым образом пересекаются так, что каждый образ-матрица с различными уровнями принадлежности может одновременно принадлежать сразу нескольким классам. Для решения задачи введена двумерная модификация самоорганизующейся карты Т.Кохонена и алгоритмы ее обучения, основанные на правилах «победитель получает все» (WTA), «победитель получает больше» (WTM) и без победителя. Если в процессе самообучения используется этап конкуренции, на каждом шаге определяется нейрон-победитель, наиболее близкий в матричной сферической метрике к предъявляемому входному образу, и используется WTA-правило обучения. Если же в процессе самообучения используется этап кооперации, в рассмотрение вводится скалярная функция соседства, например, гауссиан с матричным аргументом, и применяется WTM-правило обучения для всех нейронов сети. Сходимость WTM-процедуры обучения для всех нейронов сети обеспечивается уменьшением шага поиска и постоянным сужением рецепторного поля функции соседства, что усложняет реализацию процесса обучения для функции такого вида. Поэтому в качестве функции соседства вместо традиционных гауссианов предложено использовать функции В.Епанечникова. В работе также предложена двумерная модификация нейро-нечёткой карты Кохонена и адаптивный алгоритм ее обучения, позволяющий оценивать как параметры прототипов (центроидов) кластеров, так и уровни принадлежностей. Показано, что алгоритм обучения является модификацией нечёткого метода с-средних (FCM). Введенный матричный алгоритм обеспечивает ряд преимуществ в численной реализации перед традиционными подходами при обработке двумерных полей и массивов данных большой размерности, благодаря отказу от операций векторизации-девекторизации.