Neo-Fuzzy System with Special Type Membership Functions Adaptation and Fast Tuning of Synaptic Weights In Emotion Recognition Task

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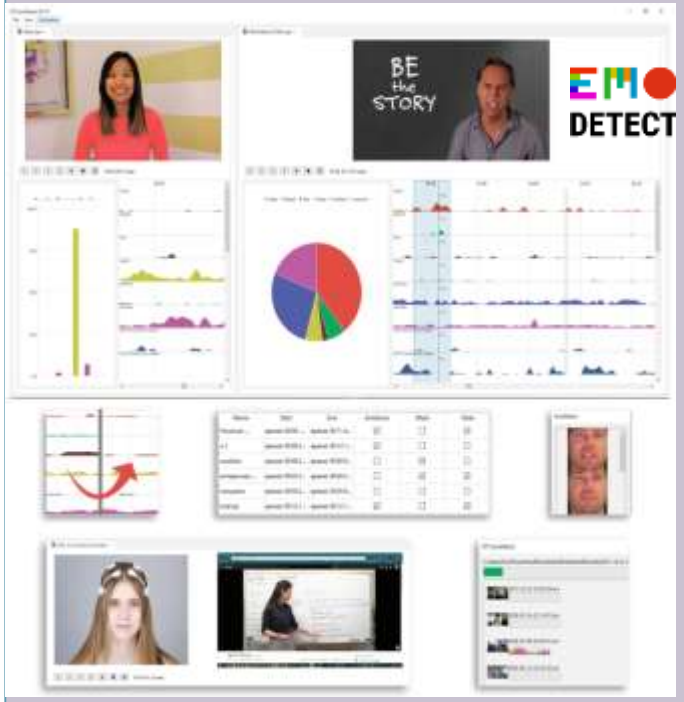
Emotion recognition task



Emotions recognition is widely used:

- education,
- digital marketing,
- automated ranking,
- recommendation systems.

Special requirements:

- high performance,
- high accuracy under conditions of significant changes in posture,
- light,
- shooting angle.

Emotion recognition task

Architecture of systems for user's emotional status automatic recognition:

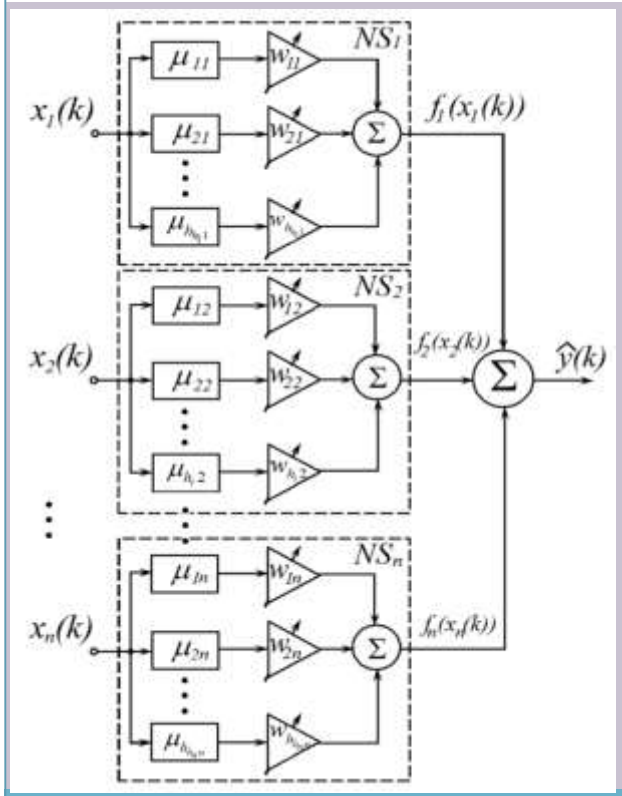
- subsystems for pre-processing,
- feature extraction,
- facial expression classification.

Convolutional neural networks:

+ Provide high classification accuracy;
– accuracy of trained networks strongly depends on diversity and volume of training dataset,
– require huge dataset volume,
– properties of datasets which are made in photo studio under same light.

The problem of adaptive system for automatic emotions recognition in real time remains actual.

ARCHITECTURE OF NEO-FUZZY SYSTEM FOR EMOTION RECOGNITION



Input vector $x(k), k = 1, 2, \ldots, N$ is fed to the input of nonlinear synapse which contains:

$\mu_{li}(x_i)$ membership functions

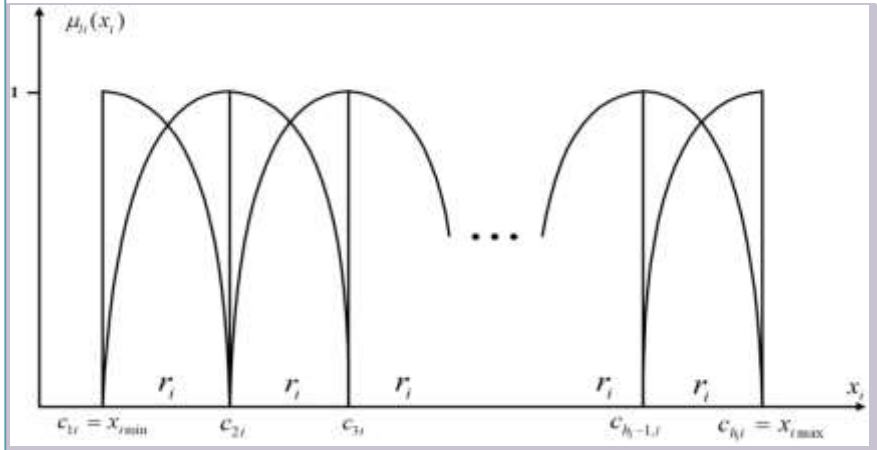
w_{li} tunable synaptic weights (are specified or in batch mode or in online mode)

In the general case, neo-fuzzy neuron implements nonlinear transformation:

$$\hat{y}(k) = \sum_{i=1}^{n} f_i(x_i(k)) = \sum_{i=1}^{n} \sum_{l=1}^{h_i} \mu_{li}(x_i(k)) w_{li}(k-1),$$

Learning: the algorithms of linear adaptive identification, including optimal by speed, robust, with smoothing.

MEMBERSHIP FUNCTIONS OF EPANECHNIKOV KERNEL TYPE



- Usually B-splines are used.
- First-order B-splines - main advantage is only two neighbouring functions are fired.
- Epanechnikov kernel membership function:

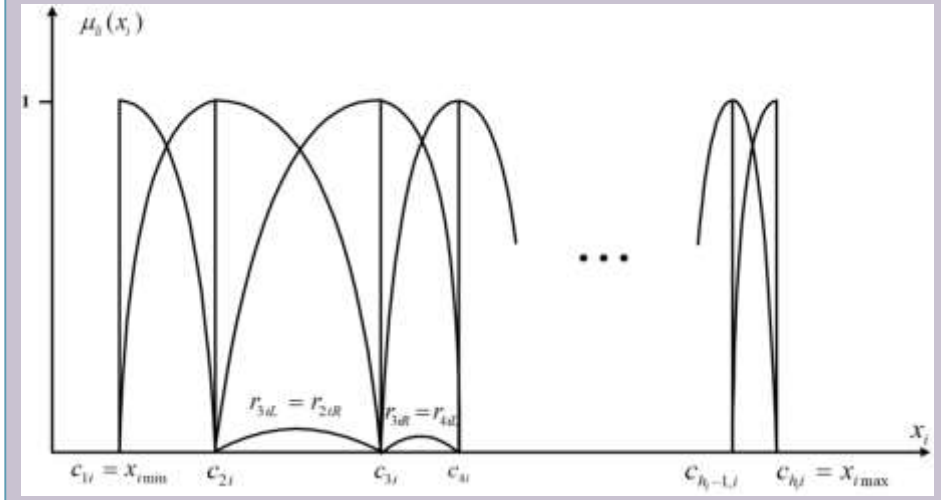
$$\mu_{li}(x_i) = (1-(x_i - c_{li})^2 r_i^{-2})\delta_{li}$$

$x_{i\min}, x_{i\max}$ interval of input signal adjustment on i-th input;

An interval between neighbouring centres: $r_i = \frac{x_{i\min} - x_{i\max}}{h_i - 1}$.

c_{li} - centres of corresponding functions and $\delta_{li} = \begin{cases} 1 & if\ |x_i - c_{li}| < r_i, \\ 0 & otherwise. \end{cases}$

MEMBERSHIP FUNCTIONS OF EPANECHNIKOV KERNEL TYPE

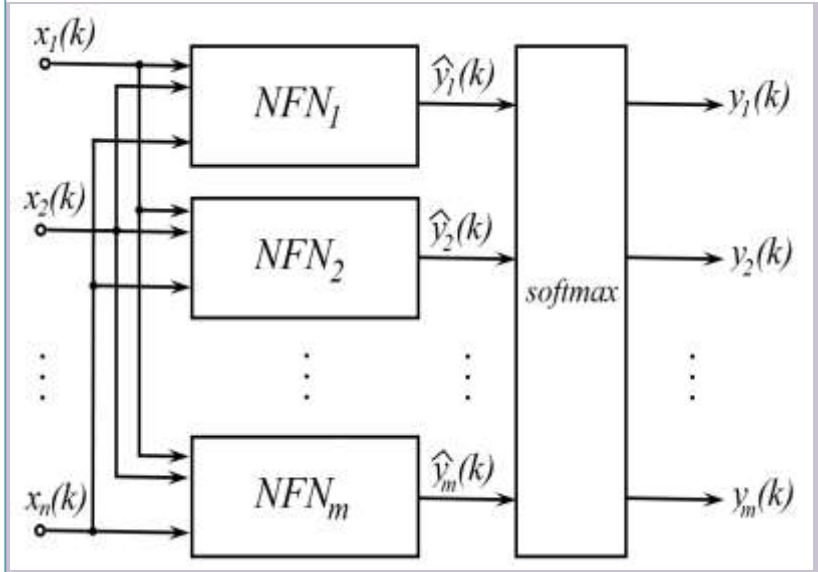


- In more general case membership functions can be distributed nonuniformly.
- Membership functions are unsymmetrical :

$$\begin{cases} \mu_{liL}(x_i) = \left[1 - \dfrac{(x_i - c_{li})^2}{(c_{l-1,i} - c_{li})^2}\right]_+, \\ \mu_{liR}(x_i) = \left[1 - \dfrac{(x_i - c_{li})^2}{(c_{l+1,i} - c_{li})^2}\right]_+ \end{cases}$$

where $[\square]_+$- a projection on positive ortant.

NEO-FUZZY SYSTEM FOR IMAGE RECOGNITION



- m connected in parallel neo-fuzzy neurons,
- their outputs are formed with softmax,
- the outputs of the neo-fuzzy system signals are formed:

$$y_j(k) = \text{softmax}\ \hat{y}_j(k) = \frac{e^{\hat{y}_j(k)}}{\sum_{i=1}^{m} e^{\hat{y}_j(k)}}$$

These signals set membership level of the observation $x(k)$ to the j-th class.

Instead of defuzzification layer, the softmax function was used.

LEARNING OF NEO-FUZZY SYSTEM

Cross-entropy as a learning criterion

$$E(k) = \sum_{j=1}^{m} E_j(k) = -\sum_{j=1}^{m} y_j^*(k) \ln y_j(k)$$

Matrix version of Kaczmarz-Widrow-Hoff can be used for the tuning of the matrix of synaptic weights and written in adaptive regularized modification:

$$w(k) = w(k-1) + \frac{y^*(k) - w(k-1)\mu(x(k))}{\gamma + \|\mu(k)\|^2} \mu^T(x(k))$$

here $\gamma > 0$ – momentm term, protected from the “exploding gradient”.

LEARNING OF NEO-FUZZY SYSTEM

Selflearning by T. Kohonen and lazy learning are used training dataset from growing. Minimal possible distance between neighbouring centers

$$r_{i\min} = \left| c_{li} - c_{l-1,i} \right|_{\min}$$

In case this condition are met, nothing will happen – new centers will not be formed

$$\left| x_i(2) - c_{1i} \right| \le r_{i\min};$$

If the second rule is met, centers are corrected according to Kohonen's rule "winner takes all"

$$r_{i\min} < \left| x_i(2) - c_{1i} \right| \le 2r_{i\min}$$

$$c_{1i}(2) = c_{1i}(1) + \eta(2)(x_i(2) - c_{1i}(1))$$

$\eta(2)$ - selflearnng rate parameter.

LEARNING OF NEO-FUZZY SYSTEM

Third condition:

$$2r_{i\min} < \left| x_i(2) - c_{1i} \right|$$

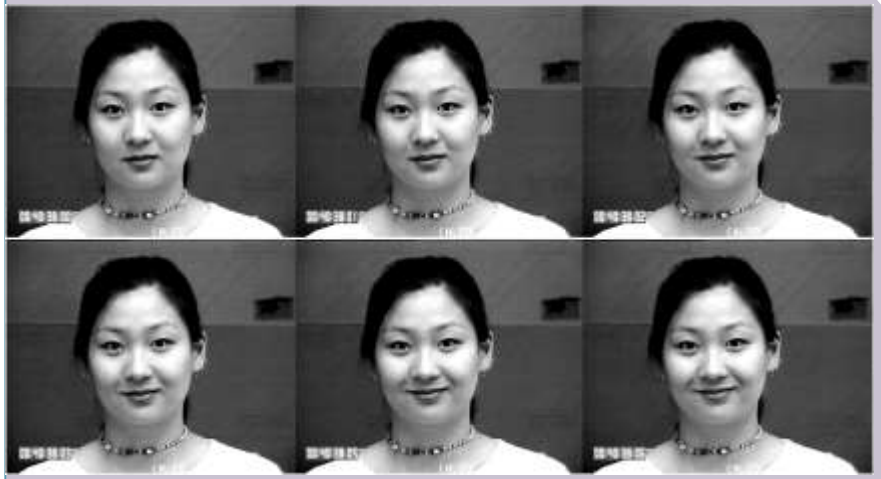
according to the lazy learning rule “Neurons at data points”:

$$c_{2i} = x_i(2)$$

The process of centres tuning take place until h_i centres will be formed, where this value is defined :

$$h_i = \frac{x_{i\max} - x_{i\min}}{r_{i\min}} + 1.$$

SIMULATIONS



Emotions:

- Anger
- Disgust
- Fear
- Sorrow
- Surprise
- Happiness
- Neutral

- Psychological Image Collection at Stirling (PICS) and Extended Cohn-Kanade (CK +) databases,
- 821 images that convey emotion development in dynamics and also contain micro-facial expressions.

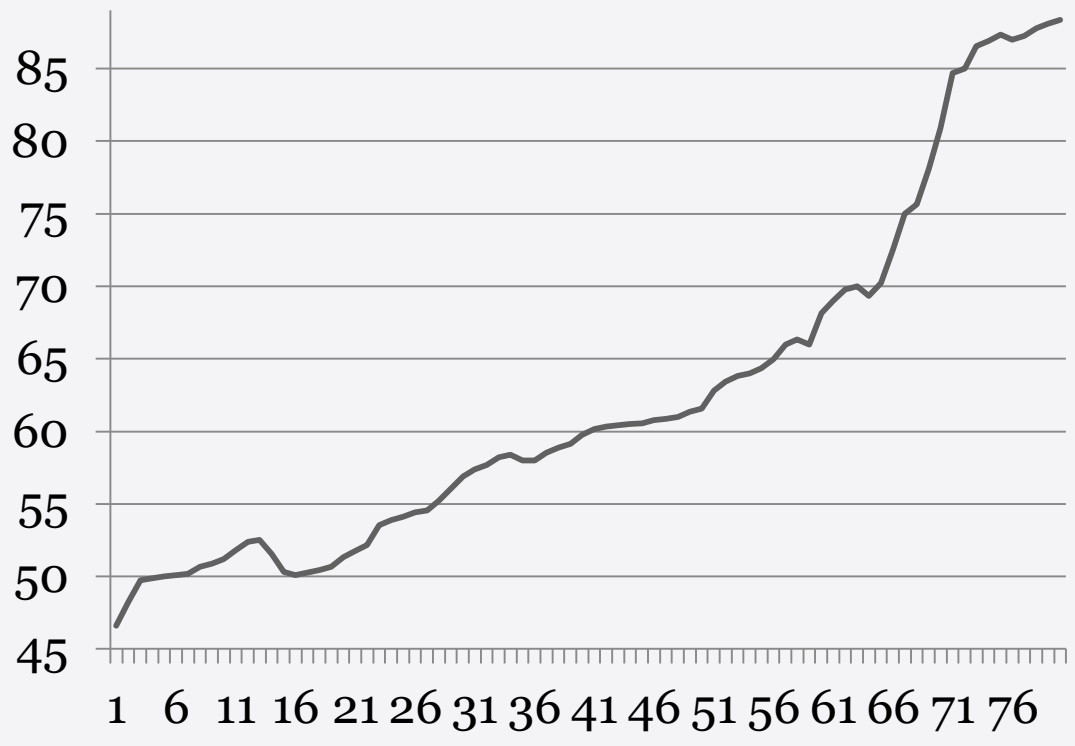
Features vector:

- X and Y coordinates 35 feature points was selected as a face model

SIMULATIONS

Experiment 1:

- 80 epochs
- a step of setting $\eta = 0{,}001$



Experiment 2:

Approach	Accuracy	Time, sec
Tunable receptive fields	93,36	91
Fixed receptive fields	85,28	64

Thanks for attention!