Neural Approach for Personalized Emotional Model in Human-Robot Interaction

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Slovakia (5 million inhabitants)
Kosice (300 000 inhabitants)
Center for Intelligent Technologies (Dpt. Cybernetics and AI)
5 permanent human staff, 25 humanoid robots, 4 PhD students
1. Motivation & System Overview

2. What is unique about our approach?

3. Technology & In vitro

4. Implementation & In vivo

5. Results & Future
How can we make the interaction with a machine (humanoid robot) easier, more enjoyable, funnier for people?
Main reasons for emotion model

Man-machine communication
Part of reasoning control (emotions vs. cognition)
"The question is NOT whether intelligent machines CAN HAVE emotions, but whether machines CAN BE intelligent without any emotions."

M. Minsky
1. Motivation & System Overview

- Visual events
- Audible events
- Touch events
- ... events
- Battery state
- Motors, processors state

External events

Events Memory

Cognition

Emotions

Events Control

Reasoning Control

Output behavior

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1. Motivation & System Overview

Emotion recognition

Robotic Expressions

Part of Human-Robot Communication

User

Machine

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2. What is UNIQUE about our approach?
different people express their feelings in different ways
2. What is unique about our approach?

A. Personalized system adapts to the concrete user
2. What is unique about our approach?

B. Evolving behaviors during interaction with users
2. What is unique about our approach?

C. 8 basic emotions \( \rightarrow \) whole emotional spectrum
2. What is unique about our approach?

D. Nao can be taught via Kinect anywhere (internet connection needed)
2. What is unique about our approach?

E. Easily preprogrammed for any humanoid-type robot
3. Technology & In vitro
3. Technology & In vitro

Plutchik’s psychological model

- Despite different forms of expression there are prototype patterns, that can be identified.
- There is a small number of basic emotions.
- All other emotions are mixed or derivative states.
- All emotions vary in their degree of similarity to one another.
- Each emotion can exist in varying degrees of intensity or levels of arousal.
3. Technology & In vitro

Plutchik’s psychological model: computational implementation

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Overlapped clusters create many types of mixed emotions from basic ones

NN recognition, Fuzzy Logic
3. Technology & In vitro

Emotion model by R. Plutchik

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3. Technology & In vitro

**membership-function ARTMAP NN**
- clustering technique with supervision
- incremental learning
- calculates the membership function (MF) of the sample from the feature space to the fuzzy class

**use:**
- classification
- optimalization of input data
- relation analysis of input data
3. Technology & In vitro: Inputs

**motion capture system**

Input pattern = M-dimensional vector \((I_1, \ldots, I_M)\)

\[ I_i = \text{position of one point of the body in time} \]
Learning

- before learning - empty memory is - no categories recorded.
- with the 1st pattern to arrive - the 1st category is created - saved in the memory
- when the 2nd pattern reaches the network, a comparison between the arrived pattern and the saved category(s) is established
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Learning

- NN compares the current input with a trained class representation (emotion) using training set.
- When receives a feature vector, deduces the best-matching category by evaluating a distance measure against all memory category nodes.
- Each new pattern is compared with all of the nodes (categories).
If new user starts to interact with the system, his/her emotions are added. The network is not learning from beginning, only this specific cluster is added to the original topology.
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Result of classification

• not a crisp decision on whether the input sample is or not a member of a particular class

• a vector of values that describes the degree of membership of this sample to all of the classes
Fuzzy cluster is considered as a fuzzy relation A in multidimensional feature space.

\[
A(\bar{x}_i) = \int_U \frac{1}{1 + \left(\frac{\bar{x}_{sk} - \bar{x}_i}{E_k}\right)^p} / \bar{x}_i,
\]

- \( j = 1, 2, \ldots, m \) - index of the dimension of input space
- \( U = X_1 \times X_2 \times \ldots \times X \) - input space
- \( n \) - number of samples in the training set
- \( i = 1, 2, \ldots, n \) - index of the current sample
- \( p \) - number of previously formed fuzzy clusters
- \( k = 1, 2, \ldots, p \) - index of the current fuzzy cluster
- \( A(x_i) \) - value of membership of sample \( x_i \) to \( k \)
- \( E_k \) and \( F_k \) - parameters of the fuzzy cluster \( k \)
- \( X_{sk} \) - center of the cluster \( k \)
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... problem

more complex shapes of real clusters... the fuzzy relation may:

1. not sufficiently cover the samples which belong to the fuzzy class
2. cover even samples which do not belong to the fuzzy cluster.

... reason

fuzzy relation cannot adapt sufficiently to the training samples
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Modified fuzzy relation

- multidimensional Gaussian probability distribution based on the covariance matrix
- able to adapt to the shape of the cluster made up from the input patterns

\[
A(\bar{x}) = e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)}
\]

$\Sigma$ covariance matrix of input samples in the dimensional feature space
$X$ vector of input sample values
$\mu$ vector of mean values
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Overlapping of clusters

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3. Technology & In vitro

Fuzzy relation for 2D input space
axes $x$ and $y$ - dimensions of the input space
axe $z$ - degree of membership of the samples to the fuzzy set (fuzzy clusters)
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1. **input layer** - 3D coordinates of body postures in time
2. **comparison layer** - partial membership functions
3. **recognition layer** - clusters - emotional expression of each of the user
   Adaptation to the concrete user
4. **mapfield layer** - classes from previous clusters – from different users
5. **cognitive layer** - similarities between classes
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Cognitive layer

similarity between classes
Jeffries-Matusita(JM) distance

\[ JM_{ij} = \sqrt{2 \times (1 - e^{-\alpha})} \]

(i, j - class identifiers of compared classes
\(\alpha\) - Bhattacharyya distance for multidimensional Gaussian distributions)

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Coefficient of similarity of each of the classes

\[ k_{\text{similarity}} = \frac{2c_{i,j}}{c_i + c_j} \]

- 0 - different classes
- 1 – identical classes

\( C_{i,j} \) number of clusters of the class \( i \) similar to our class \( j \)
\( C_i, C_j \) number of clusters of class \( i \) and \( j \)
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the degree of membership of the emotion of the new user to the existing class is 1 only 1 cluster for both of the users for Joy

the degree of membership of his/her expression to the existing expression of Joy is 0 2 clusters for expressing Joy will exist
following statement can be deducted:

“expression of Anger of User A is similar to the expression of Surprise of User B with the value of the coefficient of similarity 0.8.”

coefficient of similarity is fuzzified:

“class A is very similar/similar/not similar to the class B.”
The importance of personalization

expressions in n-dimensional space

Sadness

Joy

n-dimensional space, \( n = 48 \times \text{time} \)
4. Implementation & In vivo
Emotion recognition

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1 - Looking for pose

2 - Looking for pose

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Video

Obtaining a training set
Robotic expressions
Robotic expressions
Robotic expressions

Fear
Robotic expressions

Joy
Robotic expressions

Anger
4. Implementation & In vivo

Current real-world implementations of the system

- Children’s Dpt. of Oncology, Hospital of Kosice
- Several Schools in Kosice (age 6-12)
- Center for People with Autism
- Geriatrics (elder people)

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People with Autism See the world differently
5. Results & Future
“Is the personalized form of the emotion $E$ better understandable than the pre-programmed form of the emotion $E$?”
Results: Basic emotions

- Personalized better
- Equal to understand
- Preprogrammed better

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Results: Mixed emotions

- Personalized better
- Equal to understand
- Preprogrammed better

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Current state of the project

expand our database of emotional expressions ... CLOUD ROBOTICS!
Summary (the last slide ... )

Our modified MF ARTMAP neural network enables:

- **P**ersonalization of the robot to different users
- **R**eplicable model from human body to humanoid body
- **O**verlapped clusters create many types of mixed emotions from 8 basic emotions.
- **F**or new user – NN not learning from beginning, only this specific cluster is added to the topology.
- **I**nformation about the data structure.
  - The cognitive layer - similarity of clusters (how different people express their emotions.)
Once again ...

Visual events
Audible events
Touch events
... events
Battery state
Motors, processors state

External events

Events Memory

Internal events

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Reasoning Control

Output behavior

Emotions

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“reason leads to conclusions; emotion leads to action”

Saatchi & Saatchi
Video
System in action
“The question persists and indeed grows whether the computer will make it easier or harder for human beings to know who they really are, to identify their real problems, to respond more fully to beauty, to place adequate value on life, and to make their world safer than it now is.”
Norman Cousins – The Poet and the Computer, 1966

VIDEOS: youtube – user name: TheRiushka
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