Multi-modal Human-Computer Interaction

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Debrecen – Big Church

University of Debrecen Main Building

Road Map

- ➡ Multi-modal interactions and systems (main categories, examples, benefits)
- ➡ Turk-2 – Multi-modal chess player
- ➡ Face detection, facial gestures recognition
- ➡ Experimental results
- ➡ Examples

Defining Multi-modal Interaction[1]

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Defining Multi-modal Interaction[1]

- There are two views on multi-modal interaction:
  - The first focuses on the human side: perception and control. There the word modality refers to human input and output channels.

[1] L. Schomaker et all, A Taxonomy of Multimodal Interaction in the Human Information Processing System. A Report of the Espirit Basic Research Action 8579 MIAMI. February, 1995

- The second view focuses on using two or more computer input or output modalities to build system that make synergistic use of parallel input or output of these modalities.

Multi-modal Interaction: A Human-Centered View[2]

- The focus is on multi-modal perception and control, that is, human input and output channels.

Multi-modal Interaction: A Human-Centered View[2]

- ➡ The focus is on multi-modal perception and control, that is, human input and output channels.
- ➡ Perception means the process of transforming sensory information to higher-level representation.

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  - External chemical (taste, smell)
  - Somatic senses (touch,pressure, temperature, pain)
  - Muscle sense (stretch,tension, join position)

[3] E.R. Kandel and J.R. Schwartz, Principles of Neural Sciencies. Elsevier Science Publisher, 1981.

- Sense of balance

- Sense of balance
- Hearing

- Sense of balance
- Hearing
- Vision

Multi-modal Interaction: A System-Centered View[4]

➡ In computer science multi-modal user interfaces have been defined in many ways. Chatty gives a summary of definitions for multi-modal interaction by explaining that most authors defined systems that

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[4] S. Chatty, Extending a graphical toolkit for two-handed interaction, ACM UIST'94 Symposium on User Interface Software and Technology, ACM Press, 1994, 195–204.

- multiple input devices (multi-sensor interaction),

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- Chatty's explanation of multi-modal interaction is the one that most computer scientist use. With the term multi-modal user interface they mean a system that accepts many different inputs that are combined in a meaningful way.

Definition of the Multimodality[5]

➡ "Multi-modality is the capacity of the system to communicate with a user along different types of communication channels and to extract and convey meaning automatically."

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[5] L. Nigay and J. Coutaz, A design space for multi-modal systems: concurrent processing and data fusion. Human Factors in Computer Systems, INTERCHI'93 Conference Proceedings, ACM Press, 1993, 172-178.

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- ➡ For example, an electronic mail system that supports voice and video clips is not multi-modal if it only transfer them and does not interpret the inputs.

Two Main Categories of Multi-modal Systems

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- ➡ The goal is to use the computer as a tool.
- ➡ The computer as a dialogue partner.

The History of Multi-modal User Interfaces[6]

- ➡ Morton Heiling's Sensorama

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The History of Multi-modal User Interfaces[6]

- Morton Heiling's Sensorama. Virtual reality systems are also quite different from multi-modal user interfaces.

- Bolt's Put-That-There system. In this system the user could move objects on screen by pointing and

[6] R. Raisamo, Multimodal Human-Computer Interaction: a constructive and empirical study, Academic Dissertation, University of Tampere, Tampere, 1999.

speaking.

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- ➡ Oviatt presented a multi-modal system for dynamic interactive maps.

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- ➡ CUBRICON is a system that uses mouse pointing and speech.
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- ➡ Digital Smart Kiosk.

Benefits of Multi-modal Interfaces

- Efficiency follows from using each modality for the task that it is best suited for.

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- Perceptability increas when the tasks are facilita-

[7] M.T. Maybury and W. Wahlster (Eds.), Readings in Intelligent User Interfaces, Morgan Kaufmann Publisher, 1998.

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- ➡ Accuracy increases when another modality can indicate an object more accurately than the main modality.

- ➡ Synergy occurs when one channel of communication can help refine imprecision, modify the meaning, or resolve ambihuities in another channel.

Applications

➡ Mobile telecommunication

Applications

- ➡ Mobile telecommunication
- ➡ Hands-free devices to computers

Applications

- Mobile telecommunication
- Hands-free devices to computers
- Using in a car

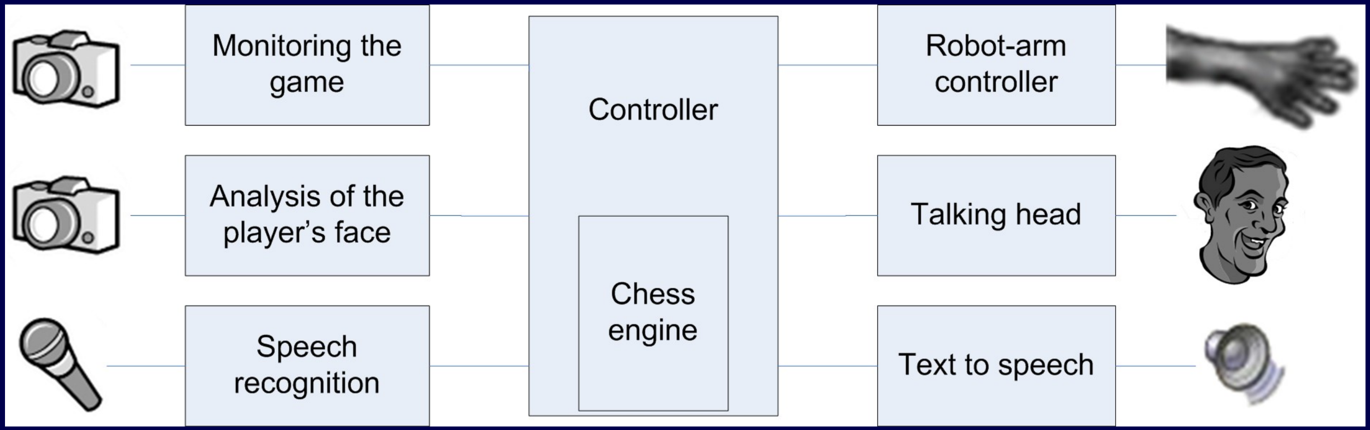
Applications

- ➡ Mobile telecommunication
- ➡ Hands-free devices to computers
- ➡ Using in a car
- ➡ Interactive information panel

Multi-modal Chess Player

Turk 2 – Multi-modal Chess Player

Turk 2 – System Components



Face Detection, Facial Gestures Recognition

Introduction

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- ➡ Automatic analysis of facial gestures is rapidly becoming an area of interest in multi-modal human-computer interaction.
- ➡ Basic goal of this area of research is a human-like description of shown facial expression.

➡ The solution of this problem can be based on the idea of some face detection approaches.

Related Research Topics

- Face detection (one face/image)

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- ➡ Face localization (more faces/image)
- ➡ Facial feature detection (eyes, mouth, etc.)
- ➡ Facial expression recognition
- ➡ Face recognition, face identification

➡ Face tracking

Problems of the Face Detection

- ➡ Pose: The images of a face vary due to the relative camera-face pose.

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- Pose: The images of a face vary due to the relative camera-face pose.
- Presence or absence of structural components (beards, mustaches, glasses etc.).
- Facial expression: The appearance of faces are directly affected by the facial expression.

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- Image orientation: Face images vary for different rotations about the optical axis of the camera.
- Imaging conditions (lighting, background, camera characteristics).

Detecting Faces in a Single Image

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- Template matching methods (A. Lanitis, C. J. Taylor, and T. F. Cootes, 1995).

➡ Appearance-based methods (E. Osuna, R. Freund, and F. Girosi, 1997), (A. Fazekas, C. Kotropoulos, I. Pitas, 2002).

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- ➡ Normalize of the window.
- ➡ Hide some parts of the face.
- ➡ Normalize of the local variance of the brightness on the picture.

➡ Equalization of the histogram.

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- ➡ Localization of the face (decision).

Face Gesture Recognition like Binary Classification Problem

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Face Gesture Recognition like Binary Classification Problem

- Let us consider a set of the facial pictures.
- Let us set up a finite system of some features related the pictures.
- It is known any pictures is related to only one class: face with the given gesture, face without the given gesture.

- ➡ The problem to find a method to determine the class of the examined picture.

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- ➡ One possible way to solve this problem: Support Vector Machine.

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➡ Statistical learning from examples aims at selecting from a given set of functions $\{f_\alpha(\mathbf{x}) \mid \alpha \in \Lambda\}$, the one which predicts best the correct response.

➡ This selection is based on the observation of l pairs that build the training set:

$$(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l), \;\; \mathbf{x}_i \in \mathbb{R}^m, y_i \in \{+1, -1\}$$

which contains input vectors $\mathbf{x}_i$ and the associated ground "truth" given by an external supervisor.

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➡ If we define the loss-function:

$$L(y, f_\alpha(\mathbf{x})) = \begin{cases} 0, & \text{if } y = f_\alpha(\mathbf{x}), \\ 1, & \text{if } y \neq f_\alpha(\mathbf{x}). \end{cases}$$

The expected value of the loss is given by:

$$R(\alpha) = \int L(y, f_\alpha(\mathbf{x}))p(\mathbf{x}, y)d\mathbf{x}dy,$$

where $p(\mathbf{x}, y)$ is the joint probability density function of random variables $\mathbf{x}$ and y.

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➡ We would like to find the function $f_{\alpha_0}(\mathbf{x})$ which minimizes the risk function $R(\alpha)$.

➡ The basic idea of SVM to construct the optimal separating hyperplane.

- ➡ Suppose that the training data can be separated by a hyperplane, $f_\alpha(\mathbf{x}) = \alpha^T\mathbf{x} + b = 0$, such that:

$$y_i(\alpha^T\mathbf{x}_i + b) \geq 1, \;\; i = 1, 2, \ldots, l$$

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where α is the normal to the hyperplane.

- For the linearly separable case, SVM simply seeks for the separating hyperplane with the largest margin.

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- ➡ We construct the optimal separating hyperplane in the feature space to get a binary decision.

Experimental Results

➡ For all experiments the package SVMLight developed by T. Joachims was used. For complete test, several routines have been added to the original toolbox.

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- ➡ For all experiments the package SVMLight developed by T. Joachims was used. For complete test, several routines have been added to the original toolbox.
- ➡ The database recorded by our institute was used.

➡ Training set of 40 images (20 faces with the given gesture, 20 faces without the given gesture.).

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- Training set of 40 images (20 faces with the given gesture, 20 faces without the given gesture.).
- All images are recorded in 256 grey levels.
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- The procedure for collecting face patterns is as follows.

- A rectangle part of dimension 256×320 pixels has been manually determined that includes the actual face.

- ➡ A rectangle part of dimension 256×320 pixels has been manually determined that includes the actual face.
- ➡ This area has been subsampled four times. At each subsampling, non-overlapping regions of 2×2 pixels are replaced by their average.

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- ➡ Similarly, 20 non-face patterns have been collected from images in the same way, and labeled -1.

Facial Gesture Database

Surprising face

Smiling face

Sad face

Angry face

Classification Error on Facial Gesture Database

Angry	Happy	Sad	Serial	Suprised
22.4%	10.3%	11.8%	9.4%	18.9%

Examples


Emotion recognization demonstration
Classify single image
Classify video
Number of faces to find:
1
Index of smallest matcher:
2
Index of largest matcher:
3
Minimum face/image area ratio (%):
6
Rescan
Tracking
Scan information
Number of faces:
1
Time of pyramid creation (ms):
15
Time of face finding (ms):
1406
Total time (ms):
1421
IRAN'S NUCLEAR PROGRAM
U.S. FEDERAL RESERVE DISCUSSES INTEREST RATE HIKES
Index Angry Sad Neutral Surprised Happy
0 false true false false false


Emotion recognization demonstration
Classify single image
Classify video
Number of faces to find:
1
Index of smallest matcher:
2
Index of largest matcher:
3
Minimum face/image area ratio (%):
6
Rescan
Tracking
Scan information
Number of faces:
1
Time of pyramid creation (ms):
0
Time of face finding (ms):
281
Total time (ms):
281
0
BOVESPA 7.42
BUY NORWEGIAN EXPLOSIVES COMPANY DYNO NOBEL FOR $1.5 BN.
Index Angry Sad Neutral Surprised Happy
0 false false true false false


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Classify video
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1
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2
Index of largest matcher:
3
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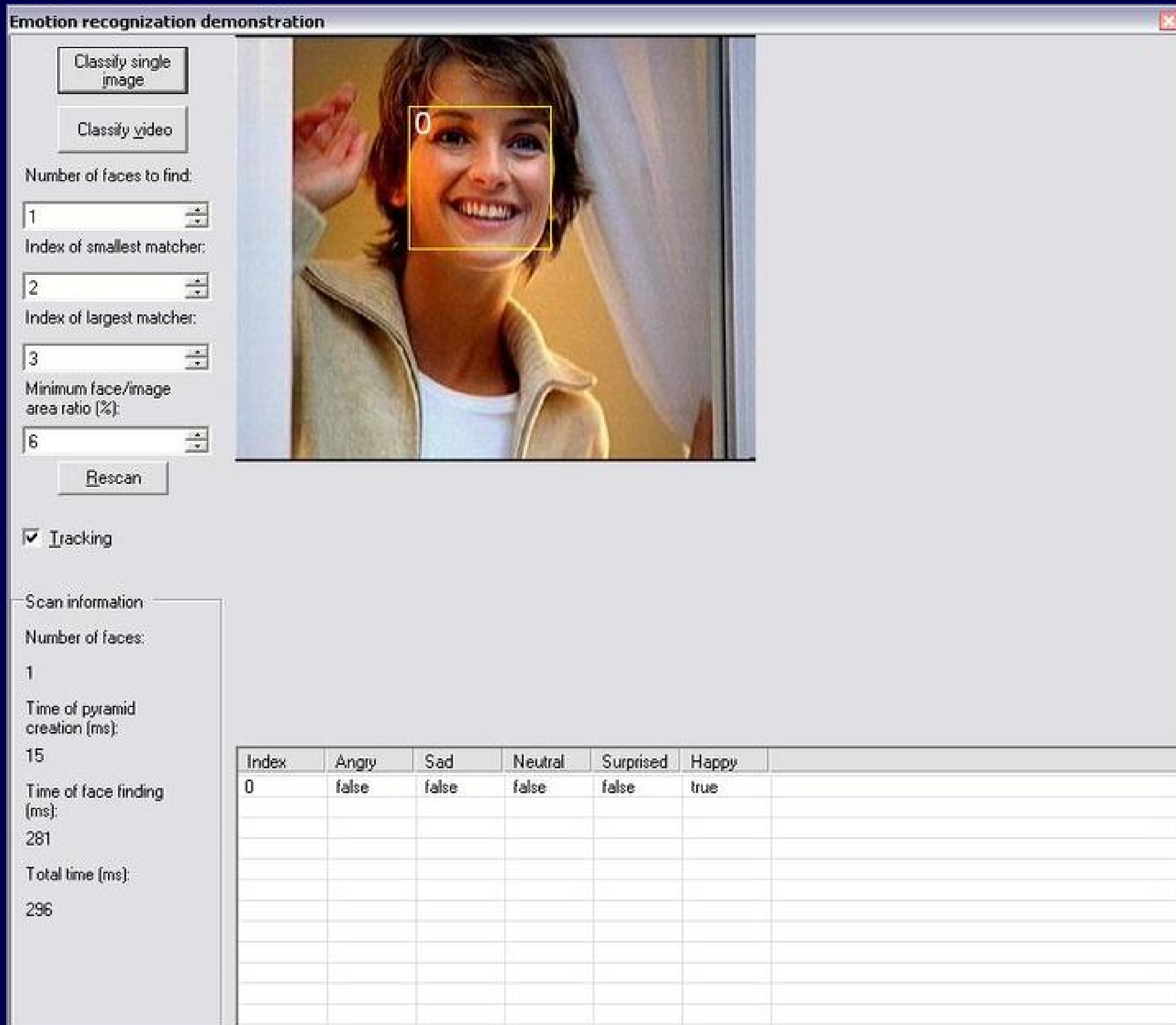
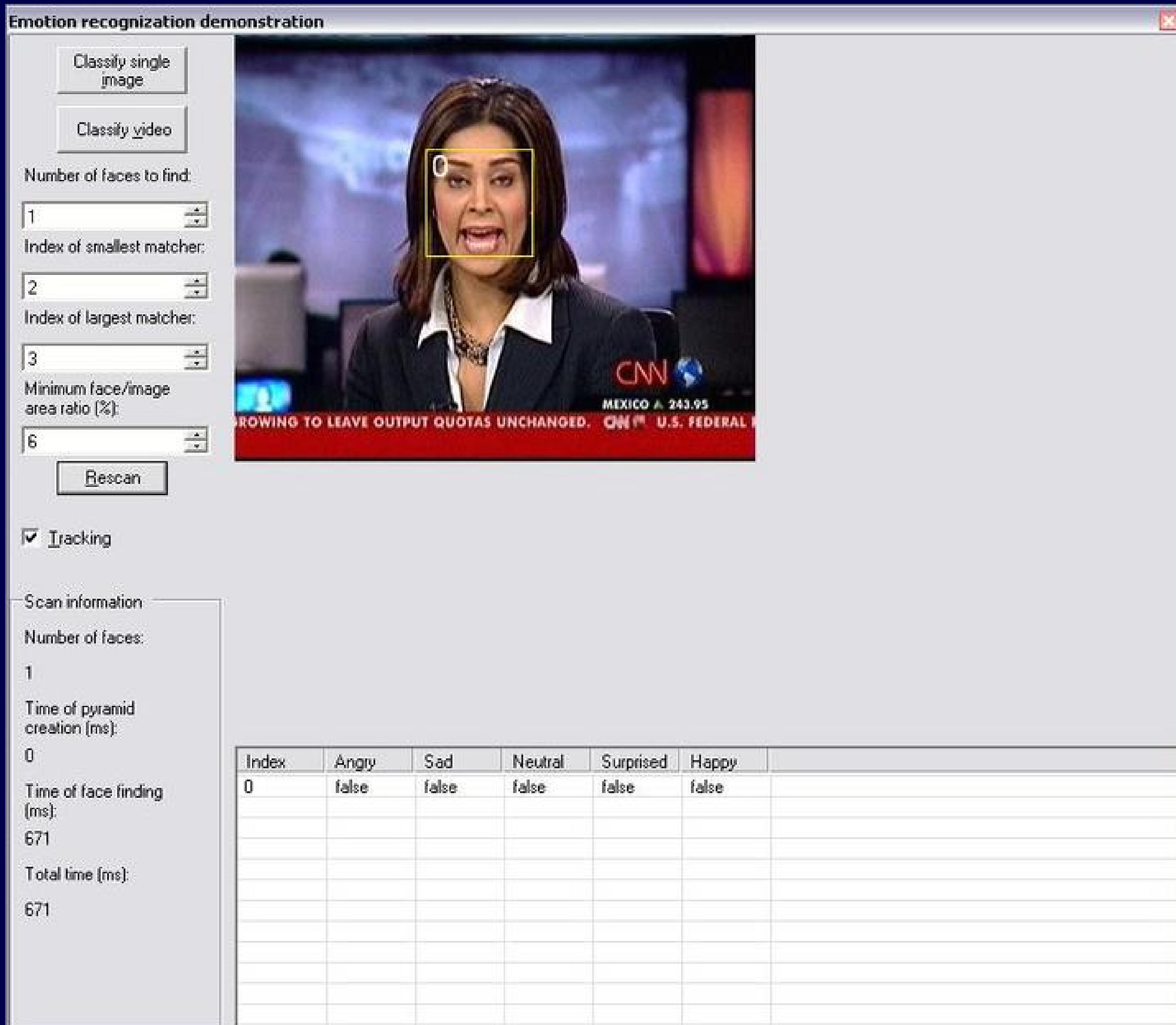
6
Rescan
Tracking
Scan information
Number of faces:
1
Time of pyramid creation (ms):
15
Time of face finding (ms):
1468
Total time (ms):
1484
Index Angry Sad Neutral Surprised Happy
0 false false false false true


Emotion recognization demonstration
Classify single image
Classify video
Number of faces to find:
1
Index of smallest matcher:
2
Index of largest matcher:
3
Minimum face/image area ratio (%):
6
Rescan
Tracking
Scan information
Number of faces:
1
Time of pyramid creation (ms):
15
Time of face finding (ms):
281
Total time (ms):
296
Index Angry Sad Neutral Surprised Happy
0 false false false false true



Emotion recognization demonstration
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Number of faces to find:
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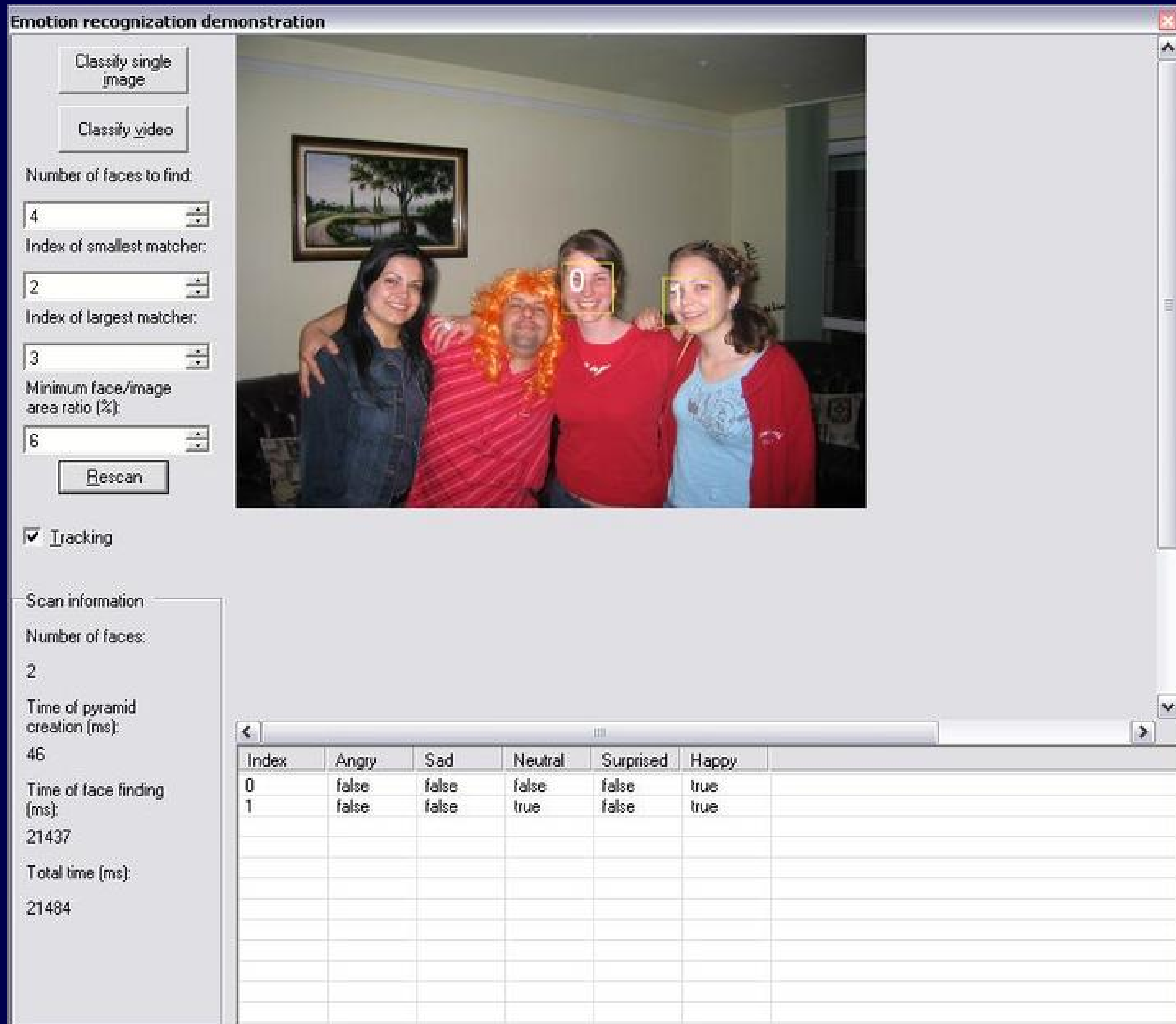
Index of largest matcher:
3
Minimum face/image area ratio (%):
6
Rescan
Tracking
Scan information
Number of faces:
1
Time of pyramid creation (ms):
0
Time of face finding (ms):
671
Total time (ms):
671
Index Angry Sad Neutral Surprised Happy
0 false false false false false


Emotion recognization demonstration
Classify single image
Classify video
Number of faces to find:
1
Index of smallest matcher:
2
Index of largest matcher:
3
Minimum face/image area ratio (%):
6
Rescan
Tracking
Scan information
Number of faces:
1
Time of pyramid creation (ms):
15
Time of face finding (ms):
1578
Total time (ms):
1593
Index Angry Sad Neutral Surprised Happy
0 false false true false false


Emotion recognization demonstration
Classify single image
Classify video
Number of faces to find:
4
Index of smallest matcher:
2
Index of largest matcher:
3
Minimum face/image area ratio (%):
6
Rescan
Tracking
Scan information
Number of faces:
2
Time of pyramid creation (ms):
46
Time of face finding (ms):
21437
Total time (ms):
21484
Index Angry Sad Neutral Surprised Happy
0 false false false false true
1 false false true false true