

## A COMPUTER VISION APPROACH FOR THE EYE ACCESSING CUE MODEL USED IN NEURO-LINGUISTIC PROGRAMMING

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*This paper investigates the Eye Accessing Cue (EAC) model used in Neuro-Linguistic Programming (NLP) and shows how image processing techniques can be used to improve the interpretation of this model. An experiment was carried out to validate the model by inducing certain eye cues using a set of questions. A simple and efficient method is proposed for automatically locating the eyes and the correspondent EAC. The relative position between the iris and the sclera is determined using a fast mechanism, based on the analysis of integral projections inside the bounding box of the eye.*

**Keywords:** Neuro-Linguistic Programming, Eye Detection, Eye Gaze

### 1. Introduction

The progress made in image processing and the increase of computational capabilities of machines over the past decades has led to new opportunities for human-computer interactions and to the development of systems capable of automatically interpreting the facial attributes of a person. Such algorithms are used in the field of people identification and description, in applications that attempt to identify the human facial expressions [1, 2], and ultimately better describe the internal emotional and psychological mechanisms of a person.

The most distinctive of the facial features are the eyes, whose movement and physical properties have been a constant source of information in multiple applications such as accurately identifying the facial expressions [3], developing eye-gaze communication solutions [4], or describing persons in terms of physical attributes such as race, age [5], or level of fatigue [6].

The movements of the eyes have been the subject of intensive psychological research and have been classified according to everyday visual tasks performed by a person [7]. Furthermore, non-visual movements of the eyes

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were analyzed by Bandler and Grinder, who introduced the Eye Accessing Cues (EAC) model as part of the Neuro-Linguistic Programming (NLP) theory [8].

NLP proposes a set of models used to describe the behavior patterns created by the interaction between the brain, the language and the body. The EAC model describes the eye-movements that are not used for visual tasks and suggests that the direction of gaze in this case can be an indicator for the internal representational system used by a person, who may think in visual, auditory or kinesthetic terms, as well as for the mental activity of that person, of remembering, imagining or having an internal dialog.

Automatic eye gaze detection increases the accuracy and flexibility of the tiresome manual labeling and is a necessary improvement in the process of psychological analyzes. But despite the extensive existing state of the art, the problem of finding a real time solution for accurately detecting the gaze direction is still unsolved, especially when considering the extra constraint of using noninvasive technology, highly recommended in psychological experiments.

This paper analyzes the problem of eye position detection in the context of the NLP EAC model. The model is described in section 2, where we also present our experiment that attempts to validate this highly controversial theory. In section 3 we propose a fast and accurate method of eye detection, which is then used in section 4 for a sclera and iris position analysis to determine the EAC. The performance of the method is discussed in section 5 and the paper ends with some conclusion and future direction of research.

## 2. NLP-EAC Model Experiment

The idea that eye movements are related to the internal representational system of a person was first introduced in [9]. A thorough study was conducted by Dilts in 1977 [10], which used electrodes to track both the eye movements and the brain wave characteristics of people, while asking them questions meant to stimulate the sense of sight, hearing and feeling with tasks involving both memory and mental construction. The results of these tests lead to the identification of the basic NLP EACs, which can be seen in Fig. 1.

Since its introduction, several studies have attempted to validate this model but the results have been inconsistent. Most of the research has provided unsupportive conclusion [11, 12, 13, 14, 15], while several studies have shown a correlation between the representational systems and the direction of eye gaze, mostly for the visual system [16, 17, 18, 19]. Most of these studies correlate the appearance of certain predicates, words associated to one of the representational systems, with the first EAC that follows them. However the cognitive response can differ from person to person and all the eye movements in response to a question should be considered.

- 1: Visual Remembered (VR)
- 2: Visual Constructed (VC)
- 3: Auditory Remembered (AR)
- 4: Auditory Constructed (AC)
- 5: Internal Dialog (ID)
- 6: Kinesthetic (K)
- 7: Visual Defocused (VD)

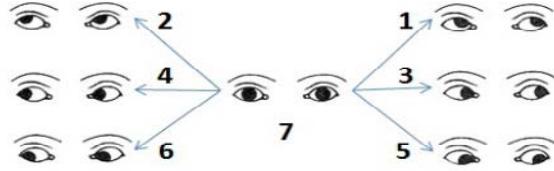


Fig. 1. Eye Accessing Cues (EACs).

Considering these observations, we have design our own experiment: a set of 29 questions has been constructed to induce certain EACs - 5 questions for VR, VC, AC and K respectively, 6 questions for AR and 3 questions for ID. The questions were recorded and played back to 10 subjects who had the flexibility of moving to the next question in their own time, while a video camera recorded them. No interviewer was present since the subject tends to look at the person asking questions, limiting the appearance of EACs. The movies were then cropped and only the sequences corresponding to the answer time were kept for analysis. These sequences were then played back 4 times slower and all the EACs were manually marked according to their type and their duration: normal visible movement, quick barely visible movement (that lasts a few frames) and pausing for a longer period in a position (for more than 3 seconds).

Table 1 shows the overall appearance of the EACs. The duration of the gaze was taken into consideration when computing the percentage, giving higher weight to longer pauses in a certain position. It can be seen that the VD EAC has a very high percentage. Although this cue is usually associated with a visual internal representation, it can in fact belong to the preferential system of the person or suggest a quick access of almost any sensory information. Based on these observations, the VD EAC was left out of further statistical analysis.

Table 1

EAC - Overall Appearance

EAC Category	VR	VC	AR	AC	K	ID	VD
Percentage [%]	7.05	10.40	9.01	11.25	11.66	14.92	35.71

For each question the mean percentage of every EAC was computed. The sum on each row is 100%. A visual representation of this information can be seen in Fig. 2, where lighter areas indicate higher percentages. Analyzing the information on each row, which shows every EAC percentage for a certain question, higher values should appear for the EAC group to which the question belongs. The expected EAC for each question group is highlighted in the figure. However, it can be noticed that the highlighted areas do not have much higher values, and the separation of the EAC groups is not that clear for all the cues.

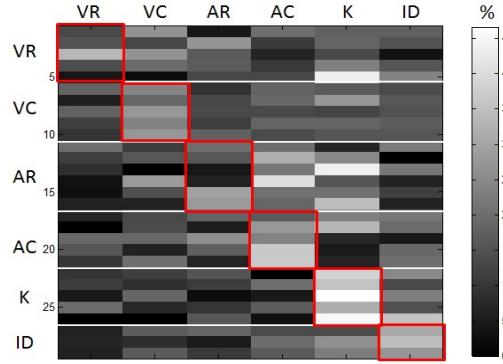


Fig. 2. Normalized (sums to 100% on rows) appearance of the EACs (columns) for each question (rows). The correspondence between gray levels and percentages can be seen in the colorbar on the left of the image: white means higher values, black means lower values.

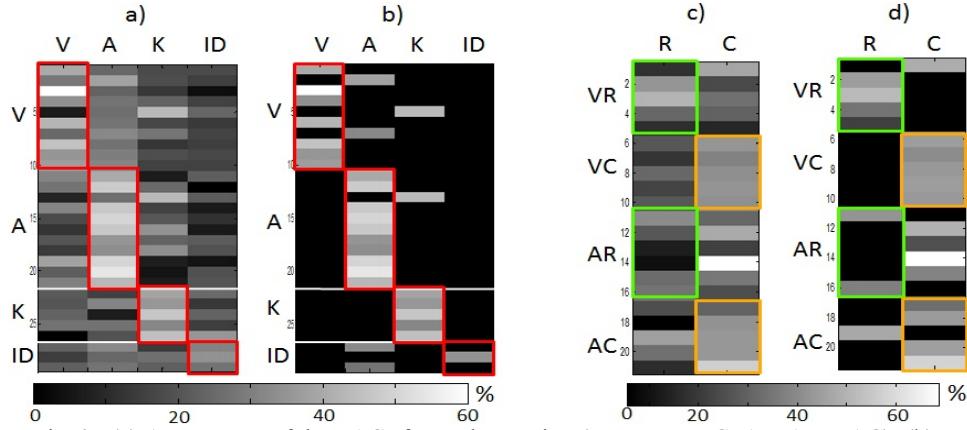


Fig. 3. (a) Appearance of the EACs for each question ( $V = VR + VC$ ;  $A = AR + AC$ ); (b) Maximum values on each line in (a); (c) Appearance of the EACs for each question ( $R = VR + AR$ ;  $C = VC + AC$ ); (d) Maximum values on each line in (c).

The next step was to evaluate the separation between the representational systems alone, without distinguishing between the mental activities of remembering and constructing. The VR/VC cues, and respectively AR/AC cues, were merged and the percentages were recomputed. In Fig. 3.(a) it can be seen that the separation is slightly more visible. Fig. 3.(b) shows only the highest percentage on each line, corresponding to the EAC that appears most often for a question. Most of the questions appear to have the expected EAC. The same strategy was applied for seeing the separation between constructing and remembering, merging VR/AR, and respectively VC/AC. A slight separation is visible in Fig. 3.(c)/(d), mainly for the visual cues. However, for most of the questions the construction activity appears to be dominant.

Some studies have shown that eye movement patterns are not universal but specific for every person [20]. Furthermore, the NLP theory claims that each person has a preferential representation system, which he may access even when asked a question that refers to another system. Based on these observations, we have attempted to see how each of the EACs is distributed over all the questions, independently of the other cues. The results can be seen in Fig. 4.(a) which shows for every EAC in what percentage it appears for every question. The sum on each column is 100%. Higher values should appear for the questions in the group of that particular cue.

We also repeated the merging process to see where is each representational system concentrated over all the questions, Fig. 4.(b). For a better visibility, in Fig. 4.(c), the percentages of the questions where a certain cue does not appear very often were discarded. Despite different eye patterns for each person, each eye cue seems to appear more frequently for the questions designed to access the respective cue.

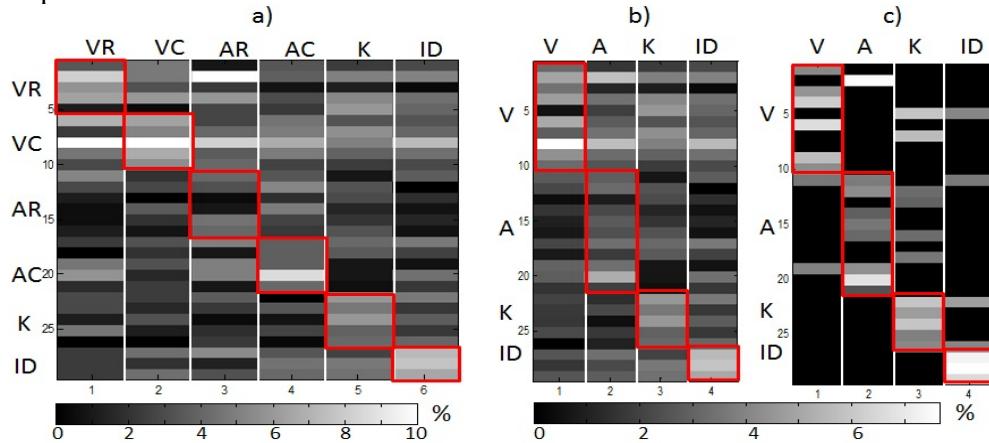


Fig. 4. (a) Distribution of each EAC over all questions (sum to 100% on columns); (b) Distribution of each EAC over all questions ( $V = VR + VC$ ;  $A = AR + AC$ ); (d) The higher values on each column in (b).

The results of our experiment have not entirely confirmed the NLP theory but a correlation between eye movements and NLP EACs was observed. The high variance of EACs over a question can be due to the complexity of the question, determining the subject to access multiple representational systems and to vary the mental activity between imagining and remembering, or carrying an internal dialog to clarify the question. A larger set of questions could be used to determine which questions are more precise and statistics should be done with more test subjects. However this is a very complex task, tiresome and prone to errors, when manual labeling of eye movements is involved. An automatic solution capable of identifying EACs is indispensable for a thorough analysis. To the author's best

information the other only known attempt for such a solution is found in [21], where the camera used to record the eye movements is mounted on the head of the subject. This is not a very practical solution and can interfere in the experiment as a distraction to the subjects. In our experiments we have used a camera mounted on a tripod, positioned at about 2 meters from the subject. In order to automatically detect the EACs, the face crop was detected [22] and the face image is then analyzed to detect the eyes and the gaze direction using a refined version of the authors' previous work [23].

### 3. Eye Detection

The first step in the EAC analysis is locating the eyes. For this task the method uses the structure of the eye: a darker area, the iris, and a whiter one, the sclera. To enhance and speed up the process, only the upper part of the face is analyzed. For locating the eyes two maps are formed, both using the blue (B) and the red (R) plane. On the blue plane the contrast between the sclera and the surrounding area is the best, as can be seen in Fig. 5(b). On the red plane the best highlight of the iris can be found (Fig. 5(c)).

The first eye map  $M_1$  is formed as:

$$M_1 = \frac{B \oplus Se_1}{R \ominus Se_1 + 1} \quad (1)$$

where  $Se_1$  is a disk-shaped structuring element used for dilation ( $\oplus$ ) and erosion ( $\ominus$ ). The result can be seen in Fig. 5(d).

The second map  $M_2$  is obtained by:

$$M_2 = (B - R) - (B - R) \circ Se_2 \quad (2)$$

where ( $\circ$ ) represents the morphological closing. The structuring element  $Se_2$  is a larger disk-shaped kernel.

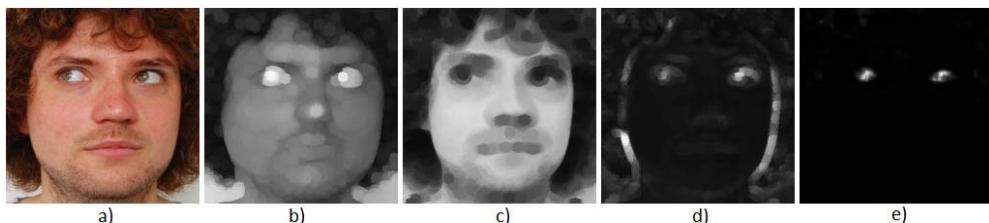


Fig 5. (a) Original image; (b) Dilatation of B plane; (c) Erosion of R plane; (d) Eye map using Eq.1; (e) Final eye map.



Fig. 6. Eye Detection Examples.

The final map  $M$  is formed by pixel-wise multiplication of the two maps:

$$M(i, j) = M_1(i, j) \cdot M_2(i, j)^2, \forall i, j \quad (3)$$

Only the maximum value given by Eq.( 3) for each eye will be kept. The result can be seen in Fig. 5(e). Fig. 6 shows some examples for the eye detection, when people are looking in different directions.

The analysis is done on a smaller scale of the image. This makes the algorithm not only simple, but also fast.

#### 4. EAC Detection

After finding a point inside each eye, the bounding box of the eye can be determined and then used for analyzing the position of the iris inside the sclera. The search area is first chosen large enough to contain the whole eye, as shown in Fig. 7(a). Inside this search area the horizontal projection, introduced in [24], is computed on  $eMap$ , a processed version of the image, highlighting the eyes:

$$eMap = 255 \cdot \left( 1 - \frac{R_{Eye}}{\overline{R}_{Eye}} \right) \quad (4)$$

where  $R_{Eye}$  is the search area's red channel and  $\overline{R}_{Eye}$  is its average.

As can be seen in Fig. 7(c) and (d), the projections have higher values in the eye area and the local minimums are searched for in order to find the upper and lower limits of the bounding box of the eye. After cropping based on limits of the horizontal projection, the same process is done on the vertical projection in order to find the right and left limits. The resulting bounding box can be seen in Fig. 7(b).

The map of the sclera  $sMap$  is formed based on the transformed blue plane  $B_{Eye}$ :

$$sMap = 255 \cdot \frac{B_{Eye} - \overline{B}_{Eye}}{\max(B_{Eye} - \overline{B}_{Eye})} \quad (5)$$

where  $\overline{B_{Eye}}$  is the mean of the blue component of the search area. This operation highlights the sclera region, while the surrounding area is darkened.

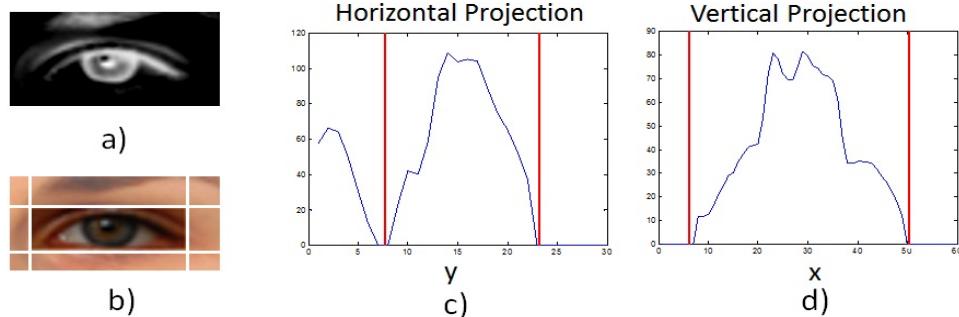


Fig. 7. (a) Highlighted eye; (b) Bounding box of the eye; (c) Horizontal projection for the eye crop; (d) Vertical projection for the eye crop.

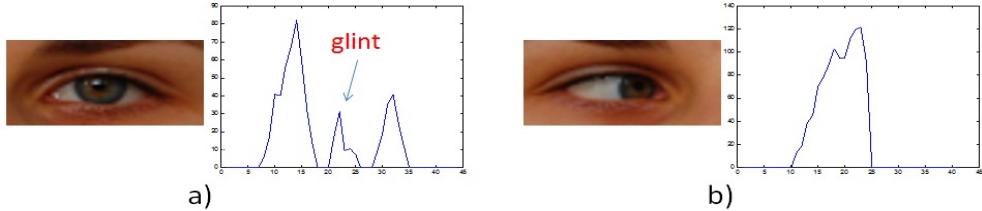


Fig. 8. (a) Vertical projection for the sclera of a centered eye; (b) Vertical projection for the sclera of an eye looking sideways.

Based on this information, the sclera is extracted using a morphological opening with a disk-shaped structuring element. The opening is needed in order to remove the artifacts caused by glint. Then the vertical projection inside the bounding box can be an indicator for the size and form of the sclera:

- If the sclera occupies a very small region of the eye crop, below 5%, then the eye is looking down. In this case a further analysis is needed to find out the horizontal position of the iris.
- If the iris has a center position, the sclera is separated into two distinct regions, as seen in Fig. 8(a).
- If the sclera is a single region, the horizontal and vertical positions of the iris must be determined.

When necessary, the overall position of the sclera inside the eye bounding box,  $(sX, sY)$ , is determined as the weighting centers of the projections:

$$sX = \frac{1}{H} \cdot \frac{\sum_{x=1}^H x \cdot PV(x)}{\sum_{x=1}^H PV(x)} \quad (6)$$

$$sY = \frac{1}{W} \cdot \frac{\sum_{y=1}^W y \cdot PH(y)}{\sum_{y=1}^W PH(y)} \quad (7)$$

where  $PV$  and  $PH$  are the vertical and horizontal integral projections for the bounding box, while  $H$  and  $W$  are the sizes of the box. We note that image projections are known to be very useful in localization of the eye center [25].



Fig. 9. Removing symmetrical objects.

A new analysis, similar to the one used for analyzing the sclera, is done on the *eMap* given by Eq.(4) to determine the position of the iris. To reduce the influence of the eyelashes on the vertical projection, a vertically reflected image is used and the symmetrical elements in the crop are removed, while preserving the asymmetrical ones as shown in Fig. 9. If the iris has a central position, the vertical position is not relevant.

At the end, the average position from both eyes is computed.

## 5. Results

In order to evaluate the accuracy of our eye detection algorithm we have used the AR Database, [26]. For 126 subjects the database provides a set of RGB images with different facial expressions, illumination conditions and occlusions, such as sun glasses, for which the eye positions have been manually marked. The accuracy measure to indicate the error of estimating the centers of the eyes is the normalized error, introduced in [27]:

$$\varepsilon = \frac{\max(d_{left}, d_{right})}{d_{eyes}} \quad (8)$$

where  $d_{left}$  and  $d_{right}$  are the Euclidian distances between the located eyes and the ones in the ground truth, and  $d_{eyes}$  is the Euclidian distance between the true eyes.

A value of  $\varepsilon \leq 0.25$  corresponds to the distance between the eye center and the eye corners, and the detection is inside the eye. In this case the detection rate was 93.18%. For a value  $\varepsilon \leq 0.1$ , the detection is inside the iris and the detection rate of the method was 79.42%.

In order to test the EAC detection method, a set of frontal face images has been selected from ten subjects, the set consisting in five images for each of the

seven EACs. The faces did not contain any occlusions in the eye area, like spectacles, strands of hair or heavy shadows.

The detection of the eye position was evaluated based on the horizontal and the vertical detection rate, Table 2. It can be seen that a good separation of the eye positions can be achieved horizontally, where the right and left positions are less confused with each other. However, the vertical positions are less separated, and a high confusion rate appears between the center position and the up position. This can be interpreted, from the EAC point of view, as a good separation between the mental activities of remembering and constructing, and a less accurate separation between the visual and the auditory internal representational system. These observations can be found as well in Table 3 that shows the detection rates for the different EACs and which pairs are more likely to be confused with each other.

Table 2

**Detection Rate for Horizontal and Vertical Positions**

Horizontal Position	Center [%]	Right [%]	Left [%]	Vertical Position	Center [%]	Up [%]	Down [%]
Center	62	15	23	Center	62	27	11
Right	6	80	14	Up	22	78	0
Left	8	28	64	Down	31	9	60

Table 3

**Detection Rate for Visual Accessing Cues**

Accessing Cues	Detection rate						
	VR [%]	VC [%]	AR [%]	AC [%]	ID [%]	K [%]	VD [%]
Ground truth	VR	72	16	9	0	0	3
	VC	6	62	0	24	0	8
	AR	25	3	54	6	3	9
	AC	2	23	0	64	0	9
	ID	2	0	23	5	50	12
	K	3	13	0	17	3	55
	VD	6	14	9	8	0	62

## 6. Conclusions

This paper has investigated the EAC model used in NLP to detect the internal representational system and the mental activity of a person, based on the position of the eyes. An experiment was carried out to evaluate this theory and the results showed there is some correlation between the eye movements and mental processes. Furthermore we have highlighted the importance of an automatic solution in analyzing eye cues and we have implemented a simple and accurate eye detection method, based on which a more detailed investigation of the eye area was possible. This analysis attempted to separate the horizontal and vertical position of an eye based on the iris and the sclera relative position. A good level of separation has been obtained for the horizontal positions of the eye, the separation of the vertical positions being slightly less accurate. Further research will be made to add an eye tracking step and include in the analysis the movement of the eyes, an important factor in interpreting the visual accessing cues. Once an automatic eye cue tracker is developed a more thorough analysis can be made to see the extent of the EAC that can be determined and induced for a person, and how such information could be used in applications such as improving interaction and learning, or overcoming psychological traumas.

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