Interest Operator Analysis for Automatic Assessment of Spontaneous Gestures in Audiometries

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Abstract: Hearing loss is a common disease which affects a large percentage of the population. Hearing loss may have a negative impact on health, social participation, and daily activities, so its diagnosis and monitoring is indeed important. The audiometric tests related to this diagnosis are constrained when the patient suffers from some form of cognitive impairment. In these cases, audilogist must try to detect particular facial reactions that may indicate auditory perception. With the aim of supporting the audiologist in this evaluation, a screening method that analyzes video sequences and seeks for facial reactions within the eye area was proposed. In this research, a comprehensive survey of one of the most relevent steps of this methodology is presented. This survey considers different alternatives for the detection of the interest points and the classsification techniques. The provided results allow to determine the most suitable configuration for this domain.

1 INTRODUCTION

Hearing loss occurs when the sensitivity to the sounds normally heard is diminished. It can affect to all age ranges, however, there is a progressive loss of sensitivity to hear high frequencies with increasing age. Considering that population aging is nowadays a global phenomenom (Davis, 1989) (IMSERSO, 2008) and that the studies of Murlow (Murlow et al., 1990) and A. Davis (Davis, 1995) point out that hearing loss is the disability more closely related to aging, the number of elder people with hearing impairment is increasingly higher.

Hearing plays a key role in the process of "active aging" (Espmark et al., 2002). Active aging is the attemp to maximize the physical, mental and social well-being of our elders. Hearing plays a key role in the process of active aging. This high impact of the hearing on the aging process makes necessary to conduct regular hearing checks if any symptom of decreased hearing is noticed.

Pure Tone Audiometry (PTA) is unequivocally described as the gold standard for audiological evaluation. Results from pure-tone audiometry are used for the diagnosis of normal or abnormal hearing sensitivity, namely, for the assesment of hearing loss. It is a behavioral test so it may involve some operational constraints, especially among population with special needs or disabilities.

In the standard protocol for a pure-tone audiometry the audiologist sends auditory stimuli to the patient at different frequencies and intensities. The patient is wearing earphones and the auditory stimuli are delivered through an audiometer to these earphones. The patient must indicate somehow (typically by raising his hand) when he perceives the stimuli. In the case of patients with cognitive decline or other communication disoders, this protocol becomes unforceable, since the interaction audiologist-patient is practically impossible. Taking in consideration that cognitive decline is highly related to age (and hearing loss is also related to age), the number of patients with communication difficulties to be assessed is potentially substantial.

Since a typical interaction question-answer is not possible, the audiologist focuses his attention on the patient's behavior, trying to detect spontaneous reactions that can be a signal of perception of the audiotory stimuli. These reactions are shown by facial expression changes, mainly expressed in the eye region. Typically, changes on the gaze direction or excessive opening of the eyes could indicate perception of the auditory stimuli. The interpretation of these reactions requires broad experience from the audiologist. The reactions are totally dependent on the patient, each patient may react differently and even a

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same patient may show different reactions at different times, since these reactions are completely unconscious. Moreover, although the audiologist has experience enough, it is a entirely subjective procedure. This subjectivity greatly limits the reproducibility and robustness of the measurements performed in different sessions or by different experts leading to innacuracies in the assessments.

The development of an automatic method capable of analyzing the patient facial reactions will be very helpful for assisting the audiologists in the evaluation of patients with cognitive decline and, this way, reducing the imprecisions associated to the subjectivity of the problem. It is important to clarify at this point that other techniques aimed at the interpretation of facial expressions are not applicable in this domain. Most of these techniques (such as (Happy et al., 2012) or (Chew et al., 2012)) are focused on the classification of the facial expressions into one of the typical expressions (anger, surprise, happiness, disgust, etc.). The facial expressions of this particular group of patients do not directly correspond to any of those categories. They are specific to each patient, without following a fixed pattern, and, as commented before, they can even vary within the same patient.

Some initial researchs have already been developed in (Fernandez et al., 2013) considering the particularities of this domain. In this work, one of the most important steps of this methodology is going to be addressed in detail: the selection of the interest points used for the optical flow (whose behavior affects every subsequent step of the methodology). Different interest point detectors are going to be studied in order to find the most appropriate for this specific problem.

The remainder of this paper is organized as follows: Section 2 presents the methodology used as base for this work and introduces the parts over which this study will be focussed, Section 3 is devoted to the experimental results and their interpretation. Finally, in Section 4 some conclusions and future work ideas are presented.

2 METHODOLOGY

As depicted in the Introduction, the development of an automatic solution capable of detecting facial movements as a response to auditory stimuli could be very helpful for the audiologists in the evaluation of patients with cognitive decline. An initial approach was proposed in (Fernandez et al., 2013), which is going to be the base for this study. A general scheme of the original methodology is shown in Fig. 1.

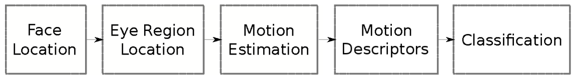


Figure 1: Schematic representation of the methodology.

This method focuses its attention on the eye region, which has been highlighted by the audiologists as the most representative for the facial reactions of these patients. This methodology is addressed in a global way since movements can occur in any area of the region. In order to address the problem from a global viewpoint but having a manageable descriptor, interest points are going to be used.

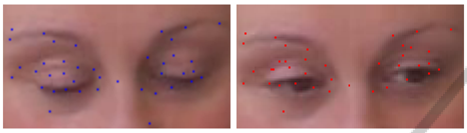
Therefore, the first steps of the methodology are aimed to the location of this particular area. The proposed approach previously locate the face region in order to reduce the search area, and then locates the eye region within the face region. Both regions are located applying the Viola-Jones object detector (Viola and Jones, 2001), the face by the application of a cascade provided by the OpenCV tool, and the eye region with a cascade specifically trained for this region. Once the eye area is located, the motion estimation begins. To that end, two separated frames are analyzed to determine the movement produced between them. The motion is estimated by applying the iterative Lucas-Kanade (Lucas and Kanade, 1981) optical flow method with pyramids (Bouguet, 2000). Once the motion has been detected, it is characterized based on several descriptors, this characterization will allow to apply a classifier which will determine the type of movement occurred. All these stages are further detailed in (Fernandez et al., 2013).

Since the results of the optical flow depend on the interest points that the method receives as input, choosing these interest points is a crucial step, since the following steps will be highly affected by the results of this stage of the methodology.

Firstly, it is important to describe the characteristics that define an interest point. Usually, these points are defined by qualities like: well-defined position on the image, mathematically well-founded, rich in terms of local information and stable to global perturbations. These properties are assigned regularly to corners or to locations where the colour of the region suffers a big change.

Considering this, we want to choose those interest points than can be easily matched by the optical flow. To select them, an analysis between different interest point detectors was conducted. Each of these methods has different foundations, and consequently, a different way of working, so the results that one provides can be very different from those provided by the others. The analysis performed in this work is further explained in Section 3.

Once the interest points are detected over the reference image, the application of the optical flow method will provide the location of these points on the second image. This means that we obtain a correspondence between the two images. In Figure 2 we can see a sample of this: Fig. 2(a) is the reference image where the detected interest points are represented in blue, Fig. 2(b) is the second image showing the correspondence of the interest points obtained by the optical flow method.



(a) (b)

Figure 2: Sample of the optical flow results: (a) Reference image with the interest points represented in blue. (b) Second image with the corresponding points obtained by the optical flow represented in red.

With this information, we can build vectors where the interest point detected on the reference image is the origin, and the correspoding point on the second image is the end of the vector. These vectors represent the direction and the amount of movement of each point of the reference image. Figure 3 shows the obtained vectors for the movement between Fig. 2(a) and Fig. 2(b). Globally, this information is going to be interpreted as the movement produced for the eye region between two images.

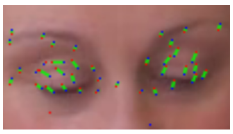
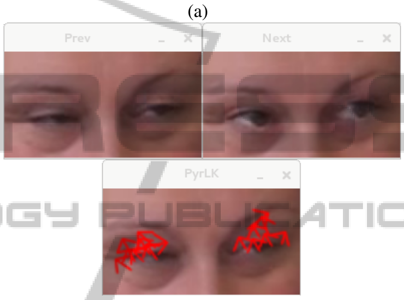


Figure 3: Movement vectors between Fig. 2(a) and Fig. 2(b).

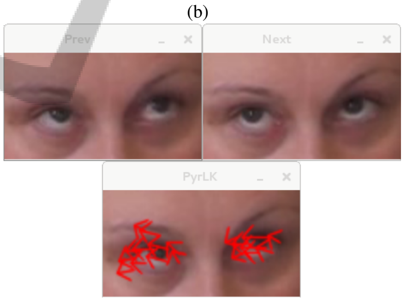
This representation can be modified into a more intuive way with vectors depicted as arrows. The arrow for a particular point represents its movement from the inicial time considered to the final one. With this representation it is possible to visually analyze the results obtained by the optical flow method.

In Figure 4 several samples of this representation can be observed. Vectors shown in this figure are the vectors with a length greater than a established threshold (those that represent significant movements), as they are a good example of how with this technique it is possible to detect the changes on the eye region. In Fig. 4(a) the gaze direction is moving towards the patient's left, this movement is detected by the optical flow and represented by the vectors that are poiting to the right. In Fig. 4(c) the movement is the opposite, the gaze direction moves slightly to the patient's right and the optical flow is still capable of detecting it. In the case of Fig. 4(b) the eyes open slightly, so in this case, vector are pointing up following the movement occurred within the region.

(a)



(b)



(c)

Figure 4: Samples of the movement vectors for different changes on the eye region: (a) gaze shift to the left, (b) eye opening and (c) gaze shift to the right.

The obtained vectors are characterized according to some features, so it is possible to obtain a descriptor that can be classified into one of our considered movements. After reaching consensus with the experts, four typical movements were identified as the most relevant: eye opening, eye closure, gaze shift to the left or gaze shift to the right. The features used for obtaining these descriptors are related with the strength, orientation and dispersion of the movement vectors, the specific way in which the descriptors are formed is detailed in (Fernandez et al., 2013). .

As mentioned, the final aim is to classify the movements produced within this region into one of the four categories previously mentioned. To that end, different classifiers have been tested too. The four established classes serve as an initial test set that allow to draw conclusions about the most suitable interest operator for this domain. These conclusions will allow to establish a foundation for moving forward and then including new classes that may be deemed relevant by the audiologists. The analysis of the different alternatives for the classification will be addressed on the next section.

3 EXPERIMENTAL RESULTS

As commented before, several interest points detectors were tested in order to find the most appropiate for this domain. The detectors tested are: Harris corner detector (Harris and Stephens, 1988), Good Features to Track (Shi and Tomasi, 1994), SIFT (Lowe, 2004), SURF (Bay et al., 2008), FAST (Rosten and Drummond, 2005) (Rosten and Drummond, 2006) and a particular version of Harris with a little modification. Also different classification techniques were tested, in order to find the better detector-classifier combination.

Video sequences show patients seated in front of the camera as in Fig. 5. As showed in the picture, the audiometer is also recorded so the audiologist can check when he was delivering the stimuli. Video sequences are Full HD resolution (1080x1920 pixels) and 25 FPS (frames per second). Despite the high resolution of the images, it is important to take into account that the resolution of the eye region will not be as optimal, and moreover, lighting conditions will affect considerably.

Figure 5: Sample of the particular setup of the video sequences.

Test were conducted with 9 different video sequences, each one from a different patient. Each audiometric test takes between 4 and 8 minutes. Considering that video sequences have a frame rate of 25FPS, an average video sequence of 6 minutes will have 9000 frames, implying a total number of 81000 frames for the entire video set. Taking into account that reactions only occur in a timely, we finally have 128 pairs of frames to be considered. Since each eye is considered separately, the test set will consist of 256 movements. These movements are labeled into four classes depending in the movement they represent (see Table 1).

Table 1: Number of samples for each class of movement.

Eye opening	Eye closure	Gaze left	Gaze right
80	82	46	48

Three different experiments were conducted ir order to find the best detector for this domain. The three experiments are:

1. Find the best classifiers.
2. Find the best configuration parameters for each interest points detector.
3. Evaluate the detector-classifier results.

3.1 Classifier Selection

In this part of the research, different classifiers were tested with the aim of selecting the three best methods for applying them on the following tests. The considered classifiers are provided by the WEKA tool (Hall et al., 2009), and they are: Naive Bayes, Logistic, Multilayer Perceptron, Random Committee, Logistic Model Trees (LMT), Random Tree, Random Forest and SVM.

To obtain this results, 18 tests were conducted for each pair detector-classifier, where each one of this test is a result of a 10-fold cross validation. Computing the average per method (without considering the detector used) we obtain the results shown in Figure 6. As it can be observed on this graph, all the methods obtain an accuracy between 60 and 75%. Worst results are observed for Naive Bayes, Logistic and Random Tree. Best results are obtained with SVM, followed by Random Committee and Random Forest, so these are going to be the three classifiers considered for the next survey.

3.2 Adjustment of Parameters

This methodology makes use of different parameters, that are going to be adjusted according to this experiment. The parameter adjustment is performed dependently on the method used. The parameters studied in this section are:

- Number of detected points: it indicates the number of points that the detector needs to select. Very

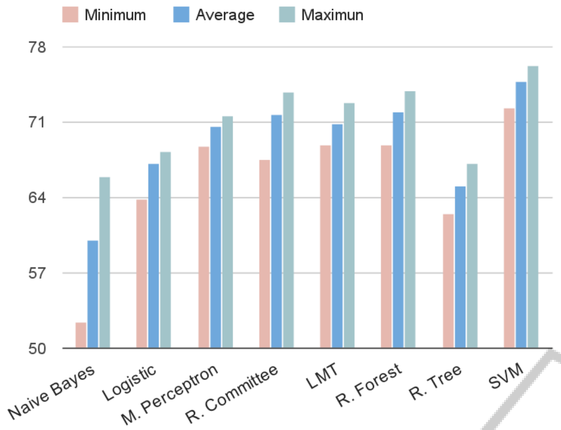


Figure 6: Minimum, maximum and average success percentage by classifier.

few points may not be enough to creat a correct motion descriptor and a number too high may introduce too much noise.

- Minimum percentage of equal points to remove the movement: sometimes, the detected motion may be due to global motion between the two frames and not to a motion within the region. This will imply a high number of vectors with the same direction and strength. With the aim of removing this offset component, the parameter λ is introduced. This parameter indicates the required minimum percentage of equal vectors to be considered a global motion, and consequently, discard them.
- Minimum length: very short vectors will not be representative of motion. In order to select the representative vectors three classes were established depending on the length of the vector: u_1 for vectors smaller than 1.5 pixels, u_2 for vectors between 1.5 and 2.5 pixels and u_3 for vector between 2.5 and 13 pixels (vectors larger than 13 pixels will be considered erroneous). Vectors in u_1 are considered too small and are not taked into account for the descriptor, while vectors in u_3 are considered relevant and are always part of the descriptors. The inclusion or not of vectors in u_2 is going to be studied on this section.

3.2.1 Harris

Harris has a particular behavior, it detects few points concentrated in areas with high contrast. The obtained results are represented in Figure 7. Each line represents a classifier (Random Committee, Random Forest and SVM), distinguishing between using only u_3 vectors (green lines) and u_2 and u_3 vectors (blue lines).

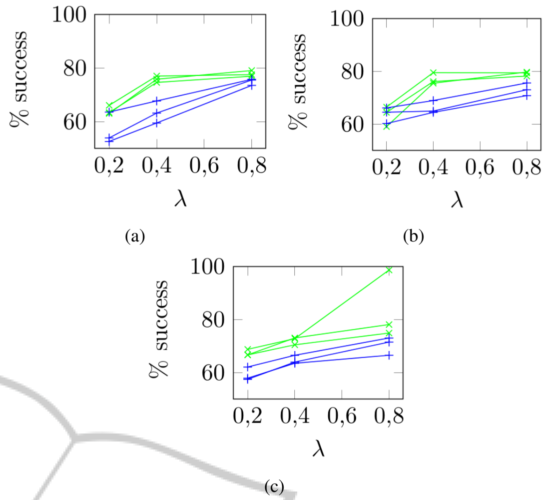


Figure 7: Classification results for Harris. Green lines for u_3 vectors and blue lines for u_3 and u_2 vectors. Each of the three lines for each color corresponds to a different classifier. (a) For 40 points of interest. (b) 80 points. (c) 160 points.

It can be observed that, the higher λ is, the better the results are. Moreover, the inclusion of the vectors in u_2 shows worse results. It can be noticed that in Fig. 7(c) there is a velue nearly the 100% of accuracy. This value is an outlier that may not be repeteable, since it breaks the tendency of the other values. However, it confirms the tendency that with higher λ values the accuracy increases.

3.2.2 Good Features to Track

This detector was specifically designed for the calculation of the optical flow. Figure 8 shows the obtained results for this classifier. As it can be observed, results are quite consistent regardless of the values of the parameters. The behavior is better for low values of λ, and also considering 80 points of interest. Although the results are very similar, including vectors in u_2 slightly increases the success rate.

3.2.3 SIFT

The SIFT detections are quite similar to the detections of Good Features to Track. Its results are also broadly similar (see Fig. 9). Unlike the previous method, in this case the results for 80 points of interest are slightly worse than for 40 or 160. The λ parameter does not affect the results too much. Inclusion of the intermediate vectors (u_2) offers also better results.

3.2.4 SURF

SURF detector is a very particular method, since it is very selective about the detected points. With these

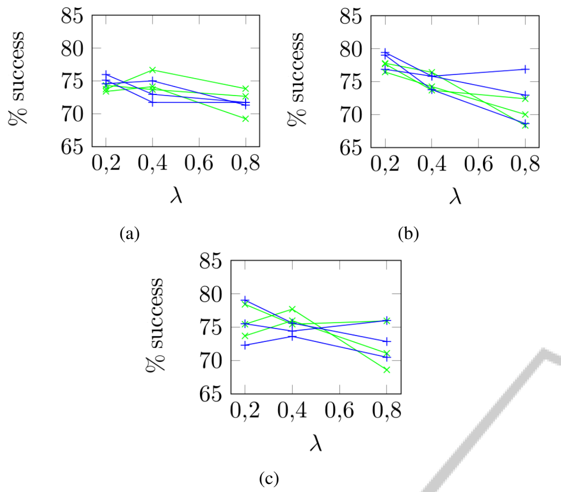


Figure 8: Classification results for Good Features to Track. Green lines for u_3 vectors and blue lines for u_3 and u_2 vectors. Each of the three lines for each color corresponds to a different classifier. (a) For 40 points of interest. (b) 80 points. (c) 160 points.

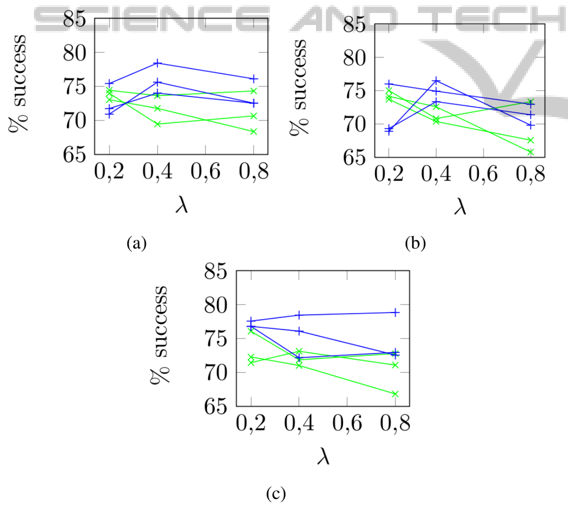


Figure 9: Classification results for SIFT. Green lines for u_3 vectors and blue lines for u_3 and u_2 vectors. Each of the three lines for each color corresponds to a different classifier. (a) For 40 points of interest. (b) 80 points. (c) 160 points.

images, it is not possible to select more than 35-40 points, even with very permissive thresholds. Due to this particularity, the only results obtained are the ones shown in Figure 10. Better results are obtained when including vectors in u_2, for which the most appropiate value of λ is 0.8.

3.2.5 FAST

The interest points detected by FAST are quite significative for this domain. Charts with the results can be

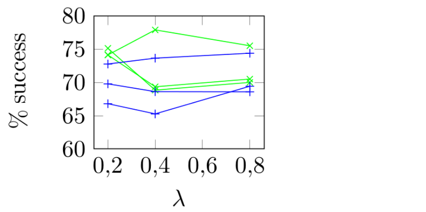


Figure 10: Classification results for SURF. Green lines for u_3 vectors and blue lines for u_3 and u_2 vectors. Each of the three lines for each color corresponds to a different classifier.

observed in Fig. 11. Regarding the length of the vectors, results vary according to the number of points considered. For 40 and 80 points, best results are obtained only considering the strong vectors (u_3), while for 160 points best results are obtained when considering vectors in u_3 and u_2. For 40 points of interest the most appropiate is a high value for λ, for 80 points the results are quite stable regardless of the value of λ, and for 160 points low values for λ offer better results.

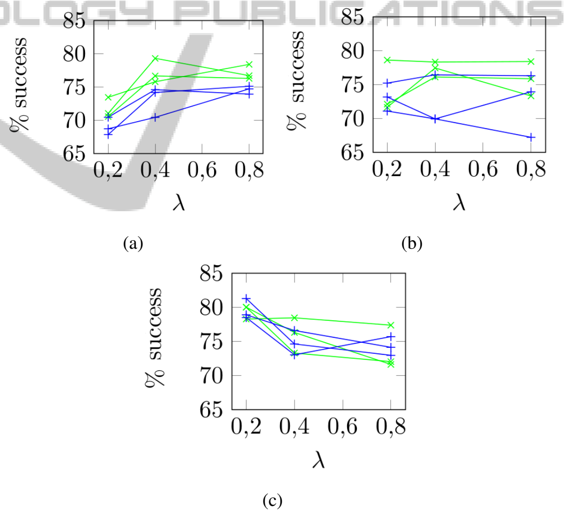


Figure 11: Classification results for FAST. Green lines for u_3 vectors and blue lines for u_3 and u_2 vectors. Each of the three lines for each color corresponds to a different classifier. (a) For 40 points of interest. (b) 80 points. (c) 160 points.

3.2.6 Harris Modified

The original Harris detector detects few points in areas with high contrast. To achieve a greater separation between the points, and therefore more representative points, a location of the local maximums is conducted. Also a thresholding is applied over the Harris image, and finally, the *and* operation is computed with these two images, obtaining this way more distributed interest points.

Results for this alternative version of Harris are charted in Fig. 12. These results are similar to the ones obtained to FAST. In the general case, better results are obtained considering only vectors in u_3. For 80 and 160 interest points, the best behavior occurs for the lower value of λ (0.2). In the case of considering 40 points, best results occur for λ equal to 0.4.

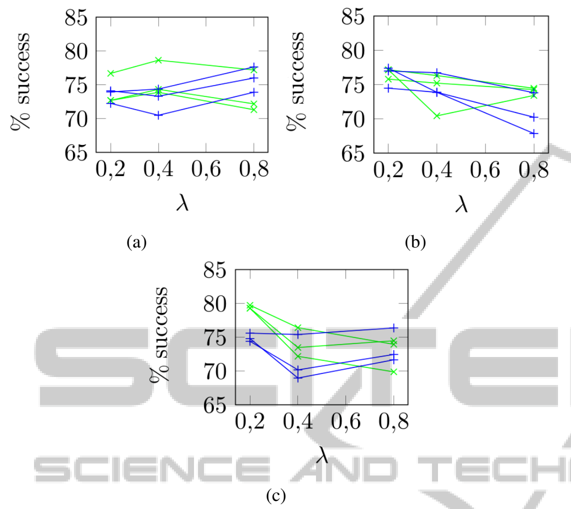


Figure 12: Classification results for Harris modified. Green lines for u_3 vectors and blue lines for u_3 and u_2 vectors. Each of the three lines for each color corresponds to a different classifier. (a) For 40 points of interest. (b) 80 points. (c) 160 points.

3.3 Final Evaluation of the Results

Once the behavior of the different methods in relation to the configuration of their paremeters has been analyzed, we are going to compare here the results of the differents methods with their best configuration. The optimum configuration parameters and classifiers for each method are detailed in Table 2.

Table 2: Optimum configuration parameters for each method.

Method	Classifier	No. points	λ	Vectors
Harris	SVM	160	0.8	u_3
Good Feat.	R. Forest	80	0.2	u_2 & u_3
SIFT	SVM	160	0.8	u_2 & u_3
SURF	SVM	40	0.4	u_3
FAST	R. Forest	160	0.2	u_2 & u_3
Harris mod.	SVM	160	0.2	u_3

Results are shown graphically for better understanding. In order to assess the capacity of each one of the interest operators in the detection of the relevant movements the obtained descriptors are compared with the ground truth of movements previously labeled by the experts.

The graph below (Fig. 13) shows the true positive and false positive rate ($T_{tp}(d)$ and $T_{fp}(d)$ respectively). It can be note that SURF has a good value for the false positive rate, but a poor value for the true positive rate. SIFT is the opposite case, it has a good value for the $T_{tp}(d)$ but poor for the $T_{fp}(d)$. The same happens with Harris, which offers intermediate values for both rates. Instead, FAST, Good Features to Track and Harris modified show good values for both rates. Good Features and FAST offer almost equivalent results, while Harris modified has a worst $T_{tp}(d)$ but it is compensated with a optimum $T_{fp}(d)$ rate.

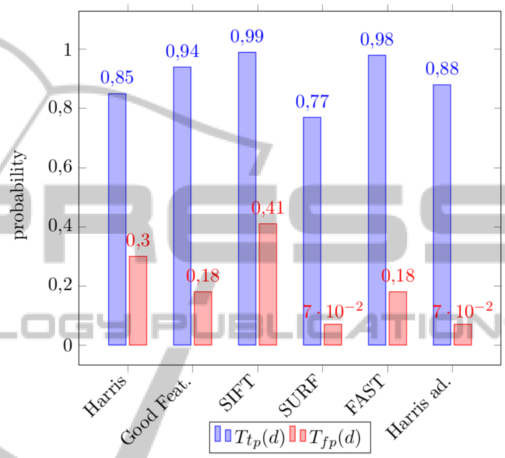


Figure 13: True positive rate ($T_{tp}(d)$) and false negative rate ($T_{fp}(d)$) for the different methods.

Given the previous results, only FAST, Good Features to Track and Harris modified are considered for the last evaluation. Figure 14 shows the true positive rate in detection ($T_{tp}(d)$), the specificity ($1 - T_{fp}(d)$) and the true positive rate in classification ($T_{tp}(c)$). All the methods have a similar value for the true positive rate in classification ($T_{tp}(c)$). FAST offers better results than Good Feature for the three evaluated measures; so between these two methods, FAST would be chosen. Comparing between Fast and Harris modified, it can be observed that the $T_{tp}(c)$ is quite similar, while the $T_{tp}(d)$ and the specificity are slightly opposite. FAST offers better results for the $T_{tp}(d)$ while with Harris better results are obtained for the specificity. The decision of choosing one or another depends on the suitable results for this domain. If we want to reduce the number of false positives Harris is the best solution, while if the true positive detections are more important, FAST is the method that should be chosen.

4 CONCLUSIONS

A methodology for supporting the audiologists in the

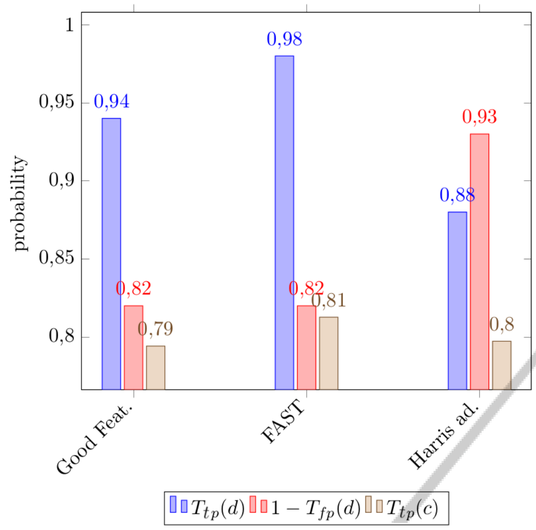


Figure 14: True positive rate ($T_{tp}(d)$) and specificity ($1 - T_{fp}(d)$) for detection and true positive rate for classification ($T_{tp}(c)$).

detection of gestural reactions within the eyes region was developed in previous research, but interest operator analysis for motion detection was not studied in detail. This paper analyzes different methods for the selection of the interest points, determines the best configuration parameters for each one of them, and it also analyzes its behavior according to different classifiers. Results obtained with new interest points detectors surpass the previous approach in terms of accuracy.

In clinical terms, the choice of a suitable interest points detector for this domain may improve the accuracy in the detection and interpretation of the gestural reactions.

Future works will involve an extension of the training dataset so a robust classifier can be trained with the configurations established by this work. This classifier may then by applied over the video sequences in order to detect the relevant movements and, thus, serve to assist the audiologists.

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