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► **To cite this version:**

B. Allaert, J. Mennesson, Ioan Marius Bilasco, C. Djeraba. Impact of the face registration techniques on facial expressions recognition. *Signal Processing: Image Communication*, 2018, 61, pp.44-53. 10.1016/j.image.2017.11.002 . hal-01644769v1

HAL Id: hal-01644769

<https://hal.science/hal-01644769v1>

Submitted on 28 Sep 2018 (v1), last revised 6 Mar 2024 (v2)

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Impact of the face registration techniques on facial expressions recognition

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Abstract

Recent methodologies for facial expression recognition have been proposed and have obtained good results in near-frontal view. However, these situations do not fairly represent in-the-wild challenges, where expressions are natural and the subject is free of its movement. This is reflected in the accuracy drop of facial expression methods obtained on recent databases. Two challenges (head pose variations and large displacements) in facial expression recognition are studied in this paper. Experiments are proposed in order to quantify the impact of free head movements using representative expression recognition approaches (LBP, LBP-TOP, HOOF). We propose an experimental protocol (SNaP-2DFe) that records, under controlled light, facial expressions with two cameras: one attached on the head and one placed in front of the subject. As in both cameras facial expressions are the same, differences in performances measured on each camera show the impact of head pose variations and large displacements on the underlying recognition approach.

Keywords: Facial expressions, Head pose variations, Large displacements

1. Introduction

2 Facial expression recognition has attracted great interest over the past decade in various do-
3 mains. Given the significant role of the face in human communication, several researches have
4 been conducted on facial expression recognition in various contexts.

5 Several systems evaluate their performances on image collections, where facial expressions
6 are played by actors, in order to obtain exaggerated facial deformations (acted expressions). Sev-
7 eral approaches [??] obtain very good results in these settings. However, these collections do
8 not fairly represent in-the-wild challenges, where expressions are natural (spontaneous expres-
9 sions), and problems like head pose variations and large displacements are frequent, as illustrated
10 in Figure ???. To answer these challenges, recently created collections [??] are mainly related
11 to interaction situations where people are free of their movements. They are more challenging
12 due to misalignment in faces, primarily caused by head motions, but also, spontaneous expres-
13 sions.

14 State-of-the-art approaches that provide good results in near-frontal view have evolved in
15 order to improve their robustness in the presence of head motions. The most commonly used

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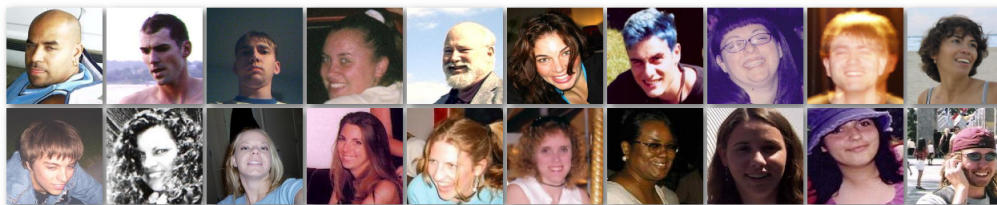


Figure 1: Faces captured in-the-wild, from GENKI-4K database [? ?].

16 solution to deal with head motions is to add a pre-processing step generally based on face reg-
 17 istration in order to obtain frontal faces [? ?]. However, these methods casually induce texture
 18 changes that are not related to the underlying expression.

19 As in-the-wild settings, expressions are not acted, their intensity is getting smaller, and,
 20 hence, the changes induced by the registration interfere with changes induced by the expres-
 21 sion itself. Indeed, spontaneous facial expressions are quite different from acted expressions in
 22 terms of facial movement amplitudes and/or texture changes. This makes them more difficult
 23 to characterize. In this context, systems based on dynamic textures may provide better perfor-
 24 mance [? ?]. Indeed, they detect subtle changes occurring on the face and do not require large
 25 changes in appearance, as texture-based or geometry-based approaches expect. However, these
 26 approaches are much more sensitive to varying head motion.

27 The question about the use and the impact of registration approaches arises especially when
 28 facial expression analysis is done in uncontrolled context. The use of registration approaches is
 29 increasing, despite a lack of evidence about their effectiveness due to the heterogeneity of the
 30 databases.

31 In this study, we address two challenges : head pose variations and large displacements
 32 in facial expressions recognition, denoted HPV and LD, respectively. In section ??, we dis-
 33 cuss the impact of HPV and LD on facial expressions recognition. In section ??, representa-
 34 tive frameworks of automatic facial expression analysis systems are introduced. Representative
 35 databases used for facial expressions recognition are reviewed in section ??. A focus on these
 36 two challenges and the performances of several approaches are compared. A common experi-
 37 mental framework using a newly created data collection covering simultaneously free (camera
 38 in front of the subject) and constrained (camera attached to the head) facial expressions is pro-
 39 posed in section ??. A series of experiments are presented in section ??, in order to quantify
 40 the performance degradation induced by HPV and LD considering representative state-of-the-art
 41 approaches. In section ??, we summarize the limits of existing methods and data collections, as
 42 well as the benefits brought by the proposed experimental framework.

43 2. Large displacements (LD) and head pose variations (HPV)

44 In interaction situations, facial expression analysis has to deal with HPV and LD challenges.
 45 LDs involve translation, cinematic blur and scale changes, whereas, HPVs involve 3D-rotations
 46 (in-plane and out-of-plane). A first encountered issue with HPV is that most of the state-of-
 47 the-art approaches which give the best results in expression recognition are not invariant under
 48 3D geometric transformations, thus computed features for the same face and the same expression
 49 vary depending on LD and HPV. For example, it is obvious that histogram-like [? ?] or dynamic

50 texture features computed from equal-sized facial grids are not invariant under translations, ro-
 51 tations and scale changes. Figure ?? shows an overview of a generic workflow often used in
 52 facial features extraction. Faces are divided into a regular grid of $m \times n$ local regions from which
 53 features can be extracted. Finally, features are concatenated into one-row vector which depicts
 54 the facial expression. HPV induces misalignment of the face (no correspondence of major facial
 55 components in each block, across the same facial image from a different point of view) and may
 56 result in mismatching between extracted features.

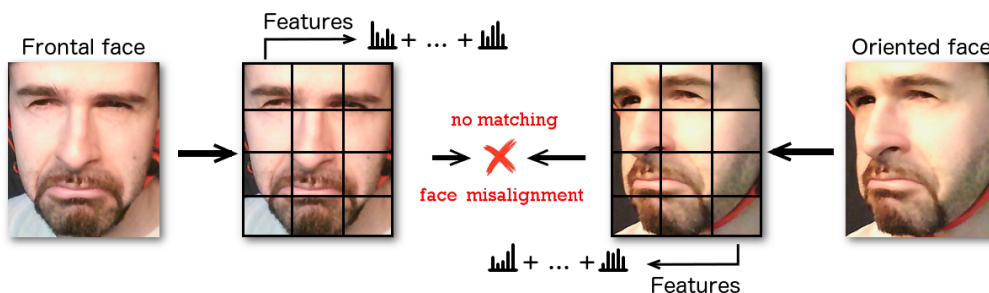


Figure 2: Example of misalignment of the face in the presence of head pose variations.

57 In order to obtain an invariance under geometric transformations, a pre-processing step which
 58 consists in registering faces is proposed in [? ?]. Face registration aims to find the transfor-
 59 mation (or the deformation) which reduces the discrepancies between two or more faces. These
 60 approaches modify facial characteristics (texture, geometry, motion) while reducing variations
 61 in translation, rotation and scale changes. However, registration induces artifacts which have a
 62 negative impact on the consistency of facial characteristics [?].

63 Another issue is encountered with LD which corresponds to important head motions between
 64 two frames. In the presence of LD, a blur effect appears on the face. This noise causes texture
 65 changes. Face registration suffers significantly under motion blur [?]. Indeed, most representa-
 66 tive face registration approaches are built on features (i.e facial landmarks), and their robustness
 67 is heavily dependent on the image quality and resolution. Hence, the performances of the regis-
 68 tration approaches may be less efficient when head motions occur. Figure ?? shows an example
 69 of mis-estimation of facial landmarks due to the blur effect caused by LD, which deteriorates the
 70 face registration.

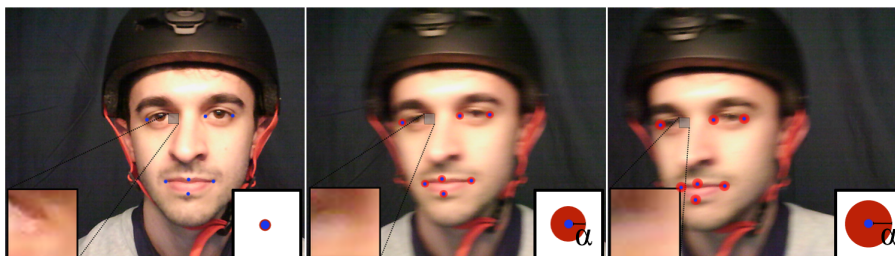


Figure 3: Poor estimation of landmarks location due to the blur effect caused by LD. α corresponds to the level of uncertainty concerning the landmarks location, which decreases sharply with the quality of the picture.

71 In brief, the presence of HPV and LD brings several challenges in the facial expression
72 analysis :

- 73 • facial misalignment due to head pose variations
- 74 • preservation of initial facial expression during face registration process
- 75 • blur effect due to rapid movements resulting in poor landmark locations

76 In the next section, we discuss solutions to the challenges listed above.

77 3. Automatic facial expression analysis

78 Automatic facial expression analysis is a complex task as the face shape varies considerably
79 from one individual to another. Furthermore, HPV and LD generate various face appearances
80 for the same person. Such variations have to be addressed at different stages of an automatic
81 facial expression analysis system. The generic facial expression analysis framework is illustrated
82 in Figure ???. First, the face is located in the frame and a registration step may be applied to
83 remove the head motion and inter-subject differences. Next, the face is analyzed to estimate
84 the remaining deformation caused by facial expressions. Then, features are extracted, and these
85 features are used in the classification part of the system.

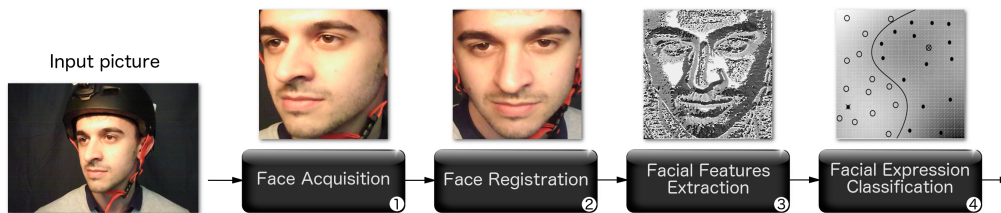


Figure 4: Generic facial expression analysis framework.

86 In the remainder of this section, we discuss the impact and the way HPV and LD are dealt
87 with face registration and facial feature extraction processing stages.

88 3.1. Face registration approaches

89 The face is usually detected and registered in order to establish the correspondence of major
90 facial components such as eyes, nose and mouth across different facial images. This aims at
91 guaranteeing invariance to geometric transformations. In the following we discuss the benefits
92 and limitations of various techniques such as eye-based registration (Eyes), as well as, more
93 evolved techniques such as shape-based registration (Shape) or 3D model-based registration (3D
94 Model).

95 *Eyes registration.* Eyes registration is the most popular strategy in near frontal-view databases
96 [? ? ?]. Eyes are detected and images are aligned and scaled with regard to the inter-pupilar
97 distance and orientation. Eyes are the most reliable facial component to be detected and suffer
98 little changes in the presence of expressions. The limitation of this approach is that eyes must
99 be well-detected. Usually, when out-of-plane rotations appear, the eyes quickly disappear and
100 additional deformations are induced, avoiding the detection of eyes.

101 *Shape registration.* Shape registration is based on 2D facial landmarks and aims at increasing ro-
 102 bustness to HPV. Extensions considering more landmarks is supposed to provide greater stability
 103 in case of individual poor landmark detections. Some approaches [? ?] only rely on landmark
 104 points located near the center of the face. The inner landmarks are mostly used to detect the
 105 face and estimate the head pose. However, these points are affected by facial deformations in the
 106 presence of facial expressions. Other approaches also take into account the contour of the face
 107 in order to exploit the information related to the geometry of the face [?]. The outer landmarks
 108 are less affected by facial deformations due to facial expressions, but they are difficult to locate
 109 in case of out-of-plane rotations. We can say that most of 2D-feature-based methods are suitable
 110 for the analysis of near frontal facial expressions in the presence of limited head motions. But,
 111 they do not cope well with difficulties brought to occlusions and out-of-plane rotation. Indeed,
 112 an image acquisition system provides only the projection of the observed scenes in a 2D plane.
 113 The projection only captures information available in front of the camera and loses out-of-plane
 114 information. Figure ?? illustrates a poor estimation of facial landmarks due to a yaw out-of-plane
 rotation, where the left part of the face disappears progressively as the face rotates.

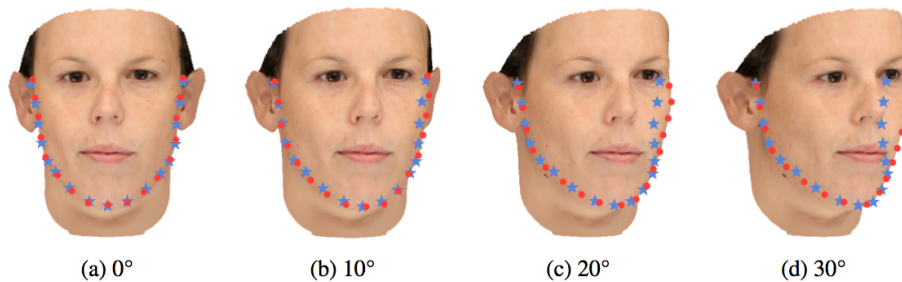


Figure 5: Similarity errors of 2D (red) and 3D (blue) facial contour landmarks under different angles [?].

115

116 *3D model registration.* Recent approaches propose robust face registration based on 3D to gener-
 117 ate a natural face image in frontal pose. Compared to 2D approaches, 3D approaches reduce
 118 the deformation of the face when facial expressions occur. Among these approaches, Zhu et al.
 119 [?] propose a robust face registration approach based on a 3D Morphable Model (3DMM). To
 120 build a 3D face model from a 2D face image, they estimate the depth of the external face region
 121 and the background.

122 **Pose registration** Landmarks are detected using facial alignment techniques from the 2D
 123 face. The authors apply landmark marching in order to solve the issue illustrated in Figure ??.
 124 Corrected landmarks on the boundary of the face are used as facial anchors. Facial anchors
 125 correspond to specific facial points that are used in order to align the 2D face on a 3D morphable
 126 model (constructed from large training data). A fitted 3D face is then generated and 3DMM
 127 coherently registers the face in front of the camera and preserves the appearance and the shape
 128 of the face. However, in case of high HPV, some regions can be hidden due to self-occlusions,
 129 as illustrated in Figure ??.

130 **Filling of occluded regions** Bad filling of the occluded region leads to large artifacts after
 131 registration and deteriorates recognition performance. To deal with self-occlusions, several ap-

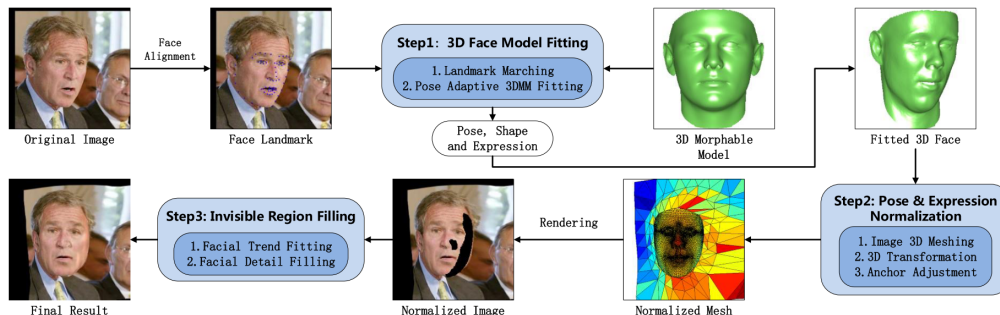


Figure 6: Face registration approach based on a 3D Morphable Model (3DMM), extracted from [?].

132 proaches use the facial symmetry or in-painting approaches [?]. The quality of these approaches
 133 depends on the size of the occluded face region and they are often not well-suited for use in un-
 134 constrained conditions (e.g illumination variation, occluding objects such as glasses and hair).
 135 Recent 3D approaches (such as [?]) use measurements over multiple frames to refine the rigid
 136 3D shape and estimate hidden facial parts (assuming that the hidden facial part was visible in the
 137 previous frames).

138 In the next section, we present the most significant facial feature extraction approaches that
 139 have been proposed in the literature.

140 3.2. Facial Feature extraction approaches

141 In the literature, there are two types of methods used to analyze facial expressions : methods
 142 based on facial static characteristics and methods based on dynamic characteristics, each of them,
 143 applied locally or globally on the face.

144 *Static texture features.* Most of facial expression recognition approaches are based on the tex-
 145 tural information [? ? ? ?]. One of the most popular method is the Local Binary Pattern
 146 (LBP) [?]. For every pixel of the image, its gray-scale value is compared with those of the eight
 147 surrounding pixels. The value of each neighbor is set to 0 if its gray-scale value is smaller than
 148 the value of the central pixel and to 1 otherwise. To reduce the dimensionality of the problem
 149 further, images are usually divided into a regular grid of $m \times n$ local regions from which LBP
 150 histograms can be extracted. Then, they are concatenated into a single histogram.

151 *Dynamic features.* The dynamic characterization of the facial texture can be achieved either by
 152 considering the changes in terms of temporal texture characteristics (extending static character-
 153 istics to temporal domain) or evaluating the changes in terms of perceived motion (by means of
 154 dense optical flow fields):

155 **Region-based temporal texture features** Dynamic texture is an extension of texture char-
 156 acterization to the temporal domain. Ambadar et al. [?] prove the importance of the dynamic
 157 texture for facial expression recognition as it allows a better analysis of physical deformation of
 158 face. Zhao et al. [?] propose an extension of the original LBP operator to the spatio-temporal
 159 domain called Volume Local Binary Patterns (VLBP). VLBP considers a block of video frames
 160 as a single 3 dimensional array of grayscale values. A simplified, more practical version of the

161 approach was proposed by its creators to make it more attractive for further usage called Local
162 Binary Patterns from Three Orthogonal Planes (LBP-TOP) [?]. LBP-TOP applies LBP on every
163 xy , x_t , and y_t slices separately. Then it averages the histograms over all slices in a single plane
164 orientation, and concatenates the resulting histograms of the three dimensions. With LBP-TOP it
165 is possible to combine motion and appearance analysis in one operator : the features histogram.

166 **Optical flow features** Optical flow measures the relative motion between two successive
167 images in a sequence. It is used to analyze facial expression [? ?] and obtains good per-
168 formances. Optical flow are dense and features encoding their local or global characteristics
169 are extracted in order to exploit the encoded motion information. For instance, Histogram of
170 Oriented Optical Flows (HOOF) feature [?] is successfully used in order to encode the distri-
171 bution of optical flows and extract global movement characteristics. HOOF feature encodes the
172 dense optical flow fields by cumulating directions binned with regard to the horizontal axis and
173 by weighting their magnitude. The weighting step aims at minimizing the noise impact on the
174 global feature. However, high HPV involves an important loss in terms of facial information and
175 it reduces the recognition rate of facial expression algorithms. Indeed, occluded face areas of the
176 current picture are defined by a set of pixels who disappear in the next picture when out-of-plane
177 rotations occur. These pixels have no correspondence within the next picture. This results in
178 motion that is not directly observable in these regions. Recent approaches use the boundaries of
179 the face (which have a high probability of being occluded in case of HPV) in order to reduce the
180 noise induced by motion discontinuities [?]. Therefore, they use fill-in methods based on the
181 motion of the neighboring regions and the physical constraints of the face (wrinkles, shape, ...)
182 [?].

183 Although dynamic textures approaches perform well in near frontal view, facial expression
184 recognition based on dynamic textures, when HPV and LD occur, is still a challenging problem.
185 Indeed, in these context stationary dynamic textures must be well-segmented in space and time.
186 The performances of these approaches depend heavily on the quality of the face registration
187 approaches to reduce facial deformations.

188 In the next section, we analyze how HPV and LD challenges are highlighted in several
189 databases commonly used to validate facial expression analysis approaches.

190 4. Facial expression databases

191 Most of facial expression systems evaluate their performances in controlled settings [? ?],
192 where the face pose is static. In these settings, expressions are exaggerated and often played
193 by actors in order to induce important deformations on the face. In contrast, some data collec-
194 tions are recorded in more natural interaction contexts, where the subject has full freedom of its
195 movement and facial expressions are spontaneous [? ? ?]. These databases, which propose
196 more natural interactions, yield more often problems related to high HPV and LD. Some acted
197 databases [? ?] have extended their data collections in order to offer a more challenging context
198 for approaches aiming to improve their robustness to in-the-wild conditions.

199 The most commonly used databases for facial expressions analysis are shown in Figure ??.
200 Figure ?? shows that the complexity of the different databases increases depending on the type
201 of expression (acted to spontaneous). Concerning the presence of LD and HPV, an indicator of
202 intensity between one and three stars (✳) depicts the ratio of data which contains LD, or HPV.


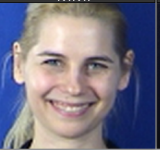

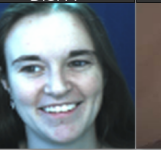
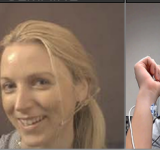

	CK+	MMI	GEMEP	DISFA	SEMAINE	RECOLA
						
Details	CK+ [28]	MMI [29]	GEMEP [4]	DISFA [31]	SEMAINE [5]	RECOLA [6]
Expressions	Acted	Acted	Acted	Spont.	Spont.	Spont.
Presence of HPV	-	*	**	*	**	***
Presence of LD	*	*	***	**	***	***

Figure 7: Commonly used databases for facial expression analysis.

203 Evolving challenges proposed in these databases reflect that the facial expression analysis
 204 in an interaction situation is a complex issue. In these contexts, the presence of HPV and LD
 205 challenges the current approaches.

206 Features previously discussed have been applied to several databases and the results are re-
 207 ported in Figure ???. Results on CK+ [?] and MMI [?] show that facial expression analysis
 208 achieve excellent performances under controlled settings where the pose is static and expressions
 209 are acted. As illustrated in Figure ??, registration approaches based on 3D models and 2D face
 210 shape are intensively used to analyze facial expressions in uncontrolled contexts. Despite the
 211 fact that these approaches provide better performances, recognition rates are still very low with
 212 regard to performances observed under controlled settings. However, in more natural interaction
 213 contexts like in GEMEP [?], DISFA [?] and SEMAINE [?], a significant drop in performance
 214 can be observed. To better visualize the performances of each registration approach on the vari-
 215 ous databases, we included in the lower part of Figure ?? two related graphics. A comparison of
 216 the approaches using average recognition or classification rates are given in Figure ??-A. Figure
 217 ??-B shows the performances of the approaches estimated using Person's cross correlation. Each
 218 color is associated with a pair of a registration approach and a database.

219 Recent databases, like SEMAINE [?] or RECOLA [?], include free head movements. Still,
 220 it is difficult to study the impact of head movements on facial expression recognition as many
 221 other parameters are changing within or between the existing databases. Hence, it is difficult to
 222 quantify the impact of issues related to LD and HPV, as well as, the registration techniques on
 223 the recognition performances. Basically, we are missing the equivalent near-frontal view data in
 224 order to measure effectively the induced deformations while correcting LD and HPV effects.

225 5. Synchronous acquisition system

226 In order to quantify the impact of free head movements on expression recognition perfor-
 227 mances, we propose an innovative acquisition system that collects data simultaneously in pres-
 228 ence and absence of head movement. Experiments are then conducted in order to estimate the
 229 impact of HPV and LD on the recognition process.

230 To address this issue, we propose a new acquisition system called : Simultaneous Natural
 231 and Posed Facial expression (SNaP-2DFe) allowing the study of the HPV and LD impact on
 232 expression recognition methods.

References	Features	Registration	Databases		Performances
Zhao <i>et al.</i> [8]	LBP-TOP	Eyes	CK+	■	ar:95.2%
Happy <i>et al.</i> [2]	Salient LBP Patches	Eyes	CK+	■	ar:94.14%
Allaert <i>et al.</i> [25]	Optical flow & Geometry	Eyes	CK+	■	cr:95.34%
Koelstra <i>et al.</i> [3]	FFDs	Eyes	MMI	■	cr:94.3%
Jiang <i>et al.</i> [1]	LPQ-TOP	Shape	MMI	■	cr:94.7%
Rivera <i>et al.</i> [16]	DNG	Shape	MMI	■	ar:97.6%
Jiang <i>et al.</i> [22]	LPQ	N/A	GEMEP	■	cr:66%
Yang <i>et al.</i> [11]	LBP,LPQ	Shape	GEMEP	■	ar:84%
Sandbach <i>et al.</i> [13]	LBP	Eyes	DISFA	■	cc:0.342
Cruz <i>et al.</i> [32]	LPQ	Shape	SEMAINE	■	ar:55%
Nicolle <i>et al.</i> [33]	Appearance & Geometry	Shape	SEMAINE	■	cc:0.46
Chen <i>et al.</i> [34]	3D Facial Shape	3D Model	SEMAINE	■	cc:0.51

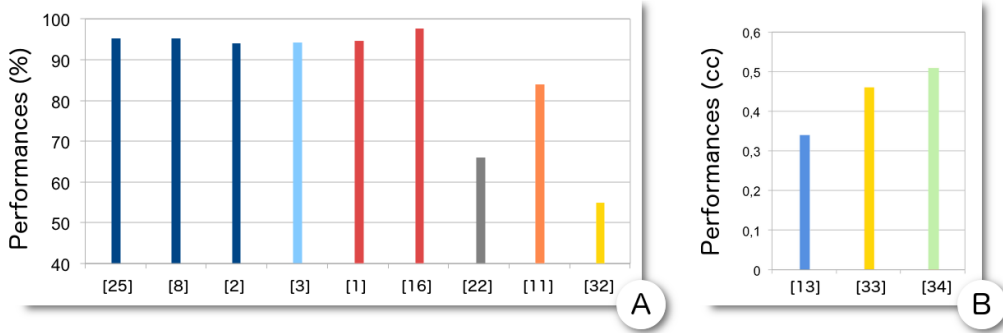


Figure 8: Recent methods to facial expression analysis in the literature. (cc: Person's cross correlation, ar: average recognition rate, cr: classification rate).

233 5.1. Acquisition system

234 Each facial expression is recorded simultaneously using a two-camera system : one camera
235 is fixed on a helmet, while the other is placed in front of the user at near-range distance. The
236 helmet camera provides data similar to CK+ [?] and MMI [?] databases, where little or no head
237 movements occur. The frontal camera provides data similar to RECOLA [?] and SEMAINE
238 [?] databases, as subjects are freely moving their head. Our database enhances measuring the
239 impact of head-movements relying on the information returned by the frontal camera, compared
240 to the helmet camera.

241 The helmet is equipped with eight LEDs, which ensure homogeneous illumination on the
242 face, even when the head is moving. It also includes a "9DOF Razor IMU" board by SparkFun,
243 which contains a 3-axis gyroscope/accelerometer/magnetometer and a micro-controller perform-
244 ing sensor fusion. Finally, it includes a camera located fifty centimeters in front of the face and
245 maintained by an aluminum rail in order to ensure global stability.

246 We use a counterweight that enhances the user's comfort and guarantees that the helmet does
247 not shift position while the user moves. It is important to guarantee that the helmet is stable in
248 order not to disrupt the user experience during the recording session. We verify that the helmet is
249 stable by computing the mean difference (in pixels) of facial landmark locations from the helmet

250 camera under neutral expression between different head poses. We have obtained very similar
 251 values regardless of the head movement. When the head is not moving we have obtained an error
 252 of 1.74 pixels. When the head is executing a diagonal movement we have obtained 1.87 pixels.
 253 In case of a Pitch, a Yaw or a Roll movement we have obtained respectively errors of 1.77 pixels,
 254 1.77 pixels and 1.95 pixels. When the head is executing a translation an error of 1.71 pixels has
 255 been reported. With regard to the values, in our understanding, errors stem primarily from the
 256 instability of landmarks location detection and not the instability of the helmet.

257 The capturing system is illustrated in Figure ???. Each participant was instructed to wear
 258 a helmet fitted with a camera (Camera 1) and to sit in front of a projection screen at about one
 259 meter away from the fixed camera (Camera 2). We recorded images using two Creative Live cam
 260 inPerson HD (Full HD 1080p at a frame rate of 30 fps) and with an uniform background. The
 261 capturing system is illustrated in the left part of Figure ???. The right part of Figure ?? represents
 262 image samples of facial expressions where the subject performs a pitch movement. The first two
 263 lines correspond to selected synchronous frames in time. The first line corresponds to the helmet
 264 camera (Camera 1) and the second line, to the fixed camera (Camera 2). The curve in the bottom
 265 right part of the Figure ?? represents the yaw, pitch and roll values obtained by the gyroscope
 266 during the session.

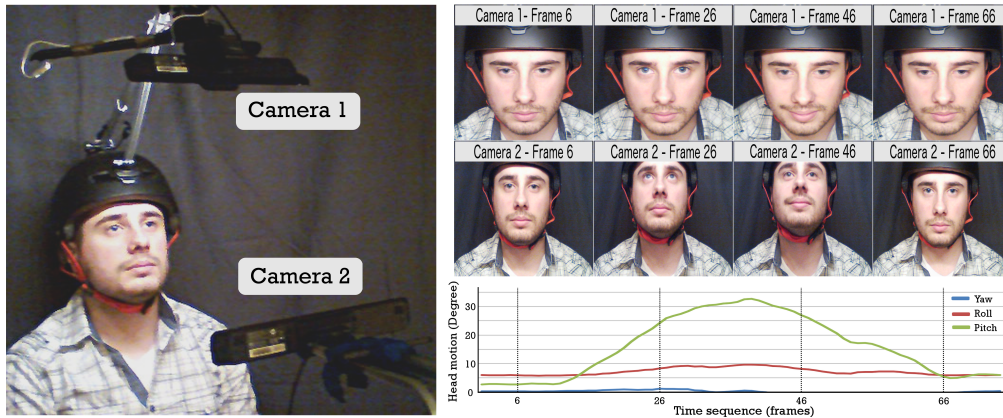


Figure 9: SNaP-2DFe system setup and example images of facial expressions recorded during a pitch movement.

267 5.2. Data acquired

268 Our preliminary database includes 840 samples collected from 10 subjects. Each video cor-
 269 responds to a combination of one facial expression and a sequence of uniform head movements.
 270 In each sequence, the user follows a specific pattern of movement that corresponds to one of the
 271 following animations : one translation on x (T_x - corresponding to LD motions), combined with
 272 three rotations (roll, yaw, pitch - corresponding to HPV motions).

273 In static sequences, the user does not move the head, in order to collect data for head-posed
 274 facial expression analysis. In diagonal sequence, the user moves the head while combining
 275 translations and rotations. Movement ranges are large: translations go up to more than 150mm
 276 in any axis from the starting point, and rotations can reach 40 degrees.

277 For each subject, we have six animations combined with seven expressions (Neutral, Hap-
278 piness, Sadness, Anger, Fear, Surprise, Disgust) from two cameras, which makes a total of 84
279 videos for each subject (42 with HPV and 42 without HPV).

280 The subjects were instructed to express emotions. Yet, as the subjects were not actors, in
281 some situations, expressions recorded show spontaneous expressions characteristics: low inten-
282 sity, limited facial deformations, various ways of expressing a given expression. In some other
283 situations, the subjects were acting a different expression than the one they were asked for. How-
284 ever, this is not an issue at this point, as our main concern is to evaluate classification results
285 comparing the near frontal-view data and the HPV-LD data of the same underlying expression.

286 The data collected is freely available for research purposes and can be downloaded on de-
287 mand from <http://www.cristal.univ-lille.fr/FOX/>.

288 In order to assess the impact of face registration approaches on the recognition of facial ex-
289 pressions, the next section discusses the results of different registration methods on the collected
290 SNaP-2DFe database.

291 6. Experimentation

292 Several experiments are conducted in the following. Firstly, we measure the ability of the
293 registration techniques to simulate frontal pose images (like the ones produced by the helmet
294 camera) from the static camera. As a reminder, the helmet-camera is a fixed frontal camera,
295 where no head motion appears except the facial expressions. The characteristics of the face are
296 stable during the sequence. This means that no registration step is necessary. In the experiments
297 presented in Section ??, we evaluate the capabilities of face registration approaches to reduce the
298 discrepancies between faces from frontal and non-frontal settings.

299 Secondly, we study the ability of registration techniques to preserve the original facial defor-
300 mations produced by the underlying expression. In Section ??, expression recognition classifiers
301 are trained from the helmet-camera images and we measure the ability of registration techniques
302 to bring non-frontal images in frontal settings with regard to the frontal classifiers. In Section ??,
303 we conduct a series of experiments, where the classifiers are trained from the registered images,
304 in order to evaluate if the deformations, induced by the registration, preserve distinctive features
305 for expression classification. Finally, we conduct an experiment in order to evaluate the impact
306 of the registration deformation with regard to specific expressions in Section ??.

307 6.1. Evaluation of registration quality

308 In order to clearly illustrate the quality of the registration process we provide a qualitative
309 and a quantitative evaluation. The qualitative evaluation illustrates visually the deformation in-
310 duced by the registration process, whereas the quantitative evaluation measures the geometric
311 and structural similarity between the registered face (from the fixed camera) and the near-frontal
312 view face (from the helmet camera).

313 6.1.1. Qualitative evaluation

314 Figure ?? shows a qualitative comparison of three face registration techniques on different
315 head poses extracted from SNaP-2DFe database (e.g. frontal pose, translation on x (Tx), roll,
316 pitch, yaw and diagonal). To deal with near frontal face, Eyes registration is more adapted
317 because this registration will not cause facial deformations and the locations of feature points are
318 rather stable. However, severe out-of-plane rotation downgrade the precision of feature points

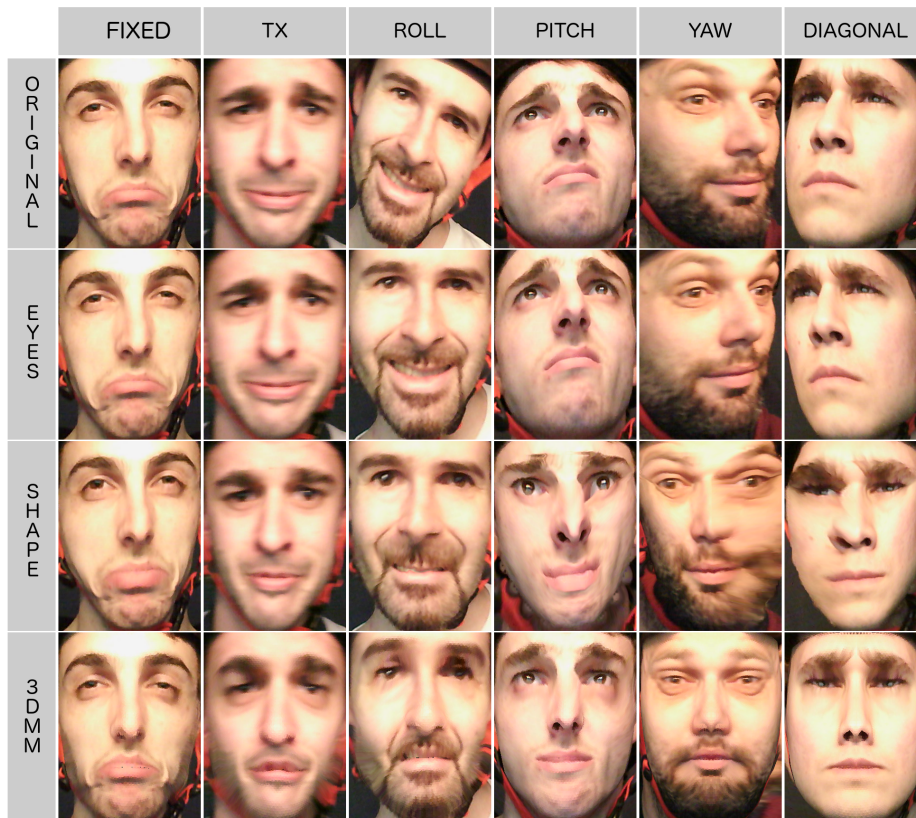


Figure 10: Example of different facial registration approaches on each animation.

319 localization process. This causes strong face deformations. In this case, recent approaches based
320 on 3D face model seem better suited than other approaches. 3DMM method illustrated here is
321 based on facial symmetry reconstruction [?]. Thanks to the reconstruction of occluded face
322 regions, this approach allows rebuilding faces in the presence of out-of-plane rotations.

323 6.1.2. Quantitative evaluation

324 *Experimental Setup.* In order to evaluate the quality of face registration process, we use the
325 structural similarity index method (SSIM) [?]. SSIM compares local patterns of pixel intensi-
326 ties that have been normalized for luminance and contrast. The face geometry delivers good
327 information for some facial expressions, but fails in detecting subtle motions, that can be de-
328 tected only by observing skin surface changes. From our point of view, SSIM is appropriate to
329 measure the errors of the face registration for facial expression recognition. SSIM formula is
330 based on three comparison measurements : luminance (l), contrast (c) and structure (s). The
331 measure between two local regions x and y of common size $N \times N$ is :

$$SSIM(x, y) = l(x, y).c(x, y).s(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_x\sigma_y + c_2)(2cov_{xy} + c_3)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)(\sigma_x + \sigma_y + c_3)}. \quad (1)$$

332 where μ_x and μ_y are the average of x and y , σ_x^2 and σ_y^2 are the variance of x and y , and cov_{xy}
 333 is the covariance of x and y . Three variables $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$, $c_3 = c_2/2$ stabilize the
 334 division with weak denominator, where L corresponds to the dynamic range of the pixel-values
 335 and $k_1 = 0.01$ and $k_2 = 0.03$.

336 SSIM is applied on each animation of SNaP-2DFe, after using different registration ap-
 337 proaches, based on : Affine Transformation on eyes location (Eyes), facial shape deformation
 338 using moving least squares [?] (Shape) and 3D Morphable Model [?] (3DMM). Results are
 339 reported in Table ??.

340 *Result Analysis.* 3DMM registration approach gives the best overall results, with mean similarity
 341 of 61.33% over all animations. Eyes and Shape registrations are very similar. Eyes registration
 342 approaches suit better in-plane geometric transformation (fixed, translation and roll) than Shape
 343 registration. Both present limitations due to the fact that they only exploit the visible 2D in-
 344 formation, whereas 3DMM registration achieves better results in out-of-plane conditions (pitch,
 345 yaw, diagonal). In all cases, registration approaches improve the SSIM metrics in challenging
 346 conditions even though it does not guarantee a perfect match between the two cameras.

Registration	Fixed	Tx	Roll	Pitch	Yaw	Diagonal	Mean
None	53.30	47.88	48.68	46.34	46.54	51.14	48.98
Eyes	58.26	55.06	55.29	54.57	52.01	55.79	55.16
Shape	55.25	53.49	52.29	57.40	54.44	57.67	55.09
3DMM	64.72	61.81	58.17	60.52	58.47	64.29	61.33

Table 1: SSIM (in percentage) applied on each animation, with different face registration approaches.

347 Considering the results, face registration approaches may not ensure a perfect similarity be-
 348 tween faces. But still, we expect that they encode expression-related artifacts that might still
 349 differentiate between expressions.

350 In the next section, we study the impact of the facial deformation induced by face registration
 351 approaches to facial expression recognition.

352 6.2. Evaluation of registration impact on expression recognition

353 We provide experimental results about the impact of facial registration on expression recog-
 354 nition performance when free head movements occur.

355 In this context, we try to measure the capacity of the registration method to induce facial
 356 deformation that can cope with classifiers learnt from the near-frontal recordings provided by the
 357 helmet camera.

358 *Experimental Setup.* The next series of experiments are conducted using LIBSVM [?] with the
 359 Radial Basis Function kernel for classification. Each expression is classified into one of the seven
 360 classes : Neutral, Anger, Fear, Disgust, Happiness, Sadness, and Surprise. Assuming the face
 361 region is well aligned after applying different face registration approaches, we use a 5*5 facial
 362 block based approach to extract the features. We consider commonly used static (LBP) and
 363 dynamic (LBP-TOP, HOOF) texture features for classifying expressions. The implementation
 364 of LBP and LBP-TOP were taken from [?]. HOOF feature extraction was reimplemented by
 365 us considering the algorithm described in [?]. Expression recognition rates are computed by
 366 employing the 10-fold cross-validation protocol.

367 In the first experiment, near-frontal faces recorded with the helmet camera are used for the
 368 training step. This first experiment allows to evaluate the performance of the different approaches
 369 in good conditions (not involving HPV or LD). The characteristics of the face are stable during
 370 the sequence, hence no registration step is necessary. All registration approaches were applied
 371 on each animation. The expression recognition classifier is trained using images captured in
 372 near-frontal settings using the helmet camera.

373 *Result Analysis.* The results for the different configurations : fixed versus helmet camera, no
 374 registration versus various registration approaches on the fixed camera are given in Table ?? . A
 375 first look at the results obtained in Table ?? shows that the originating camera and face regis-
 376 tration approaches have significant impact on the performances. In the following we discuss the
 377 impact of the features, the registration method as well as the originating camera.

	Helmet camera	Fixed camera			
Method	Original data	Original data	Eyes	Shape [?]	3DMM [?]
LBP	75.52	30.55	47.46	47.76	51.34
LBP-TOP	78.34	19.44	49.12	44.62	46.93
HOOF	83.21	17.38	50.01	42.16	48.73

Table 2: Facial expression recognition rates while using different face registration approaches.

378 **Impact of the originating camera** Results reported in first column of Table ?? show that
 379 the state-of-the-art methods are suitable for the analysis of facial expressions when the head is
 380 not moving. However, in the presence of HPV and LD, images provided by the fixed camera are
 381 poorly classified as shown in the second column (Fixed Camera - Original Data).

382 **Impact of the features** The results obtained with the helmet camera show that dynamic
 383 texture features such as LBP-TOP or HOOF are more efficient than LBP. The HOOF approach
 384 obtains better performances than LBP-TOP where little or no head movement appears and proves
 385 that optical flow approaches are better suited to the facial expression analysis. However, the
 386 experiment shows a drastic fall in performances on the original data from the fixed camera. In
 387 this context, recognition rates measured with dynamic texture features have suffered more than
 388 others. Overall, these methods are much more sensitive to the presence of HPV and LD. It is
 389 important, therefore, to ensure that the face is aligned in order to maintain the benefits brought
 390 by the dynamic texture features.

391 **Impact of the registration method** When considering results obtained using various reg-
 392 istration methods on the images captured with the fixed camera (last three columns), it can be
 393 easily seen that the performances are very similar. Each column corresponds to the expression
 394 classification rate obtained after applying a different registration approach, considering respec-
 395 tively : affine transformation on eyes location (Eyes), facial shape deformation using moving
 396 least squares [?] (Shape) and 3D Morphable Model [?] (3DMM).

397 The use of registration techniques improves significantly the performances of facial expres-
 398 sion analysis when free head movements occur. Considering the results in Table ?? , the Eyes
 399 registration seems to be the most successful strategy in terms of sustainability and effectiveness

with regard to the needs of facial expression classification method. Despite the gain obtained from both Shape and 3DMM registration approaches when using LBP, these registration techniques appear to be less suited with dynamic texture features.

6.3. Evaluation of preserving distinctive facial expression deformations

In the following, we evaluate the impact of specific head motion patterns on the expression recognition rates when using LBP features. Implicitly, we quantify the capacity of registration techniques to preserve distinctive facial deformations in case of various movements typologies.

Experimental setup. The selected registration techniques have been applied and compared on each class of animations. We evaluate the impact of face registration approaches on facial expressions recognition rates and we identify the strengths and weaknesses of each. The results are given in Table ???. The training was performed on the registered images captured by the fixed camera. Hence, the trained classifier took into account the deformation induced by the registration.

Registration	Fixed	Tx	Roll	Pitch	Yaw	Diagonal
Original data	45.23	38.09	32.47	37.71	33.33	14.26
Eyes	52.38	33.33	47.61	30.95	40.47	26.19
Shape	47.61	35.71	42.85	30.95	38.02	11.90
3DMM	48.02	39.27	40.21	40.74	41.08	34.96

Table 3: Recognition rates of facial expression classification using LBP features, after face registration step.

Results analysis. The results in bold in Table ??? show the best results per registration approach obtained for specific movement patterns. While the head does not perform out-of-plane rotations, as in Fixed and Roll settings, Eyes registration provides the best results. Whereas, in case of out-of-plane rotations the 3DMM registration performs better.

The Eyes registration is the most suitable in frontal (fixed) settings. Indeed, in near-frontal view condition, a simple in-plane rotation aligns the face. This solution preserves the geometry of the face. However, this method is not working well in case of LD or HPV. Thanks to the reconstruction of the occluded face region, 3DMM approach obtains the best results when out-of-plane rotations occur. However, the reconstruction system is based on a face mirroring technique, which sometimes has negative impact on the induced facial expression.

6.4. Evaluation of per-expression registration impact

We have conducted a complementary study about measuring the impact of the registration techniques with regard to the underlying expression.

Experimental setup. In the light of the previous results (see Table ???), we have selected 3DMM and Shape registrations, as well as, LBP as texture features for studying the recognition rate variations when considering various expression classes. We have constructed ROC curves using 10-fold cross-validation protocol considering the whole dataset, as well as, independent Neutral, Anger, Surprise, Happiness, Sadness, Fear and Disgust partitions. Training was conducted on the whole dataset, as well as on each expression-related partition resulting in eight different classifiers.

433 *Results analysis.* Figure ?? shows ROC curves corresponding to each expression score calculated with LBP from the helmet camera (blue) and the fixed camera after different registrations (red : 3DMM and green : Shape). With regard to the Mean Curve, faces obtained by registration show lower performances than the faces acquired by the helmet camera (see Mean Curve in Figure ??).

438 Results show that some expressions suffered severely from the registration process. Expressions like Anger, Surprise are less impacted by facial registration. This is probably due to the fact that face registration process induces less facial deformations around regions (such as eyebrows) used in the recognition process. Disgust and Fear expressions show similar behavior as Anger and Surprise, but the 3DMM registration technique seems more robust. Expressions like Happiness, Neutral and Sadness seem more impacted by the registration as regions outside the landmarks are affected (such as upper cheeks for Happiness). The drop in performances in the case of Neutral expressions underlines the fact that the deformations produced by the registration induce "false" facial expression recognition.

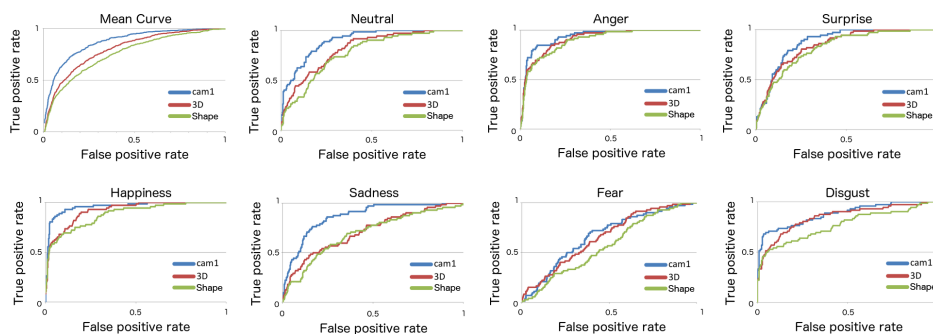


Figure 11: ROC curves for the 10-fold cross-validation protocol for LBP.

447 In the light of results from these experiments, the facial registration approaches improve the facial expression recognition in case of HPV and LD. Yet, a lot of improvements still have to be made in order to obtain comparable performances in the two settings : near-frontal views vs unconstrained head movements. The choice of face registration approach is heavily dependent on the type of head motion variation occurring in the video sequence. Mainly used for face recognition, these registration approaches do not ensure a convenient alignment persevering the expression of the face over time.

454 In the following section, we summarize the contributions of this study. From literature results (see section ??), and results obtained in our experimental settings we discuss perspectives concerning LD and HPV.

457 7. Conclusion and future works

458 In this paper we have addressed the study of the impact of registration techniques on expression recognition performances. Registration techniques are employed in order to handle HPV and LD for facial expression recognition. When analyzing the facial characteristics (texture, geometry, motion) for expression recognition, facial distortions due to misalignment degrade the

462 performances of the system. Removing distortions is a complex task. Most of the time it has a
463 negative impact on the coherency of facial characteristics (texture, geometry, motion) [?].

464 3D Model registration is constantly improving with regard to in-the-wild challenges, but
465 there is still no solution to ensure a satisfactory face registration while maintaining the facial
466 expression. Indeed, the use of face registration techniques does not seem adequate to preserve
467 the features encoding facial expression deformations. The loss in terms of precision when con-
468 sidering free head movements is partly due to the noise induced by the face registration process
469 itself.

470 In this paper, we propose an innovative acquisition system, in order to quantify the impact
471 of free head movements on expression recognition performances. Experiments on the impact
472 of well known head pose registration techniques (Eyes, Shape or 3DMM) on facial expression
473 recognition are reported. The results show that the face registration and the facial expression
474 recognition approaches are heavily dependent on the type of head motion variation. When con-
475 sidering static approaches (such as LBP), in the presence of in-plane rotations, registration tech-
476 niques based on landmarks (such as Eyes or Shape) preserves better the underlying expression.
477 However, when out-of-plane rotations occur, registration techniques based on the reconstruction
478 of 3D models seem more accurate as they preserve the underlying expressions better. Approaches
479 using dynamic features (such as LBP-TOP, HOOF) are more efficient in terms of facial expres-
480 sion analysis for frontal poses. However, these approaches do not handle well face registration
481 techniques (Eyes, Shape or 3DMM).

482 Out-of-plane rotations affect in a strong manner, the expressions recognition process. Sup-
483 porting out-of-plane rotations can be achieved either by incrementing data (as in Deep-learning
484 methods) or by registering the face representation to near frontal views. Although the first ap-
485 proach seems more popular at the present time, we truly believe that progress can be made in
486 the latter by creating innovative face registration techniques that preserve facial expression. The
487 SNaP-2DFe database can jointly be used to propose and evaluate innovative registration tech-
488 niques while reinforcing the facial expression recognition or the head pose estimation methods.

489 As an alternative to registration techniques, we think that solutions from the field of dense
490 optical flow should be explored. The enhancements of post-filtering solutions capable of regis-
491 tering the movement, by filtering out the head movement and keeping only the inner-facial local
492 movement could be done. The database proposed here may serve future works in this direction.
493 The helmet camera provides the ground truth movements while the static camera provides the
494 challenging data from where the head movements should be subtracted by future post-filtering
495 solutions.

496 8. References