Fixed Pattern Noise Analysis for Feature Descriptors in CMOS APS Images

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Abstract

This paper provides a comparative performance evaluation of local features for images from CMOS APS sensors affected by fixed pattern noise for different combinations of common detectors and descriptors. Although numerous studies report comparisons of local features designed for ordinary visual images, their performance on images with fixed pattern noise is far less assessed. The goal of this work is to develop a tool that allows to evaluate the performance of computer vision algorithms and their implementations subject to deviations of the physical parameters of the CMOS sensor. This tool will facilitate the quantification of the high-level effects produced by circuit random noise, enabling the optimization of the sensor during the design flow with specifications much closer to the application scope. Likewise, this tool will provide the electronic designer with a relationship between high-level algorithm accuracy and maximum fixed pattern noise. Thus the contribution is two-fold: i) to evaluate the performance of both local float type and more recent binary type detectors and descriptors when combined under a variety of image transformations, and ii) to extract relevant information from circuit-level simulation and to build a noise model to be employed in the design of the feature descriptor evaluation. The utility of this approach is illustrated by the evaluation of the effect of column-wise and pixel-wise fixed pattern noise at the sensor on the performance of different local feature descriptors.

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1. Introduction

The emergence of powerful, low-cost, and energy-efficient processors has enabled the incorporation of practical computer vision capabilities in embedded systems, mobile devices, PCs, and the cloud. As a result, in the coming years, there will be a rapid proliferation of integrated vision technologies in many different application scenarios. In this context, we can define a smart camera as an autonomous vision system integrating an image sensor and all the required electronics to analyze the targeted scene. Concerning the image sensor, while analog realizations could still be in use, we focus in this work on digital image sensors, typically from a Charge-Coupled Device (CCD) or a Complementary Metal-Oxide-Semiconductor (CMOS) sensor array that operates with visible light – though many vision systems can also detect other types of energy (IR, sonar, etc). CCD sensors exhibit some advantages over CMOS image sensors in terms of image quality and dynamic range. However, our interest lies in CMOS image sensors, which now account for more than 90% of the market¹. This predominance is heavily influenced by the massive market of camera phones demanding lower cost, better integration and higher speed. In CMOS Active Pixel Sensor (APS) imagers [1], the performance of the pixel depends on technology parameters and the physical design rules of the manufacturing process. Thus, the enhancement of pixel performance can be achieved by optimizing process-related parameters. This in turn calls for the development of technology-based models to evaluate particular processes and to optimize the electrical and physical performance of the imaging pixel.

The physical implementation of different primitives for capturing and processing the image suffers from deviations from the ideal behavior. On the one hand, the implementation of a sensor is not free of noise sources. For example, the reset operation gives rise to thermal noise in a three-transistor active pixel sensor (3T APS) shown in Figure 1 [2, 3]. The photodiode has to be reset before the charge accumulation begins again, so that in each new cycle the photodiode reset circuit forms a low pass filter RC with the equivalent

¹<https://www.embedded-vision.com/technology/cameras-sensors>

resistance of the reset transistor on, generating a component of noise kTC . Another example is found in the transistors that act as a voltage follower in the same 3T-APS pixel, which show across-chip deviations in their threshold voltage [3]. This introduces a permanent deviation that is specific to each pixel. It is known as fixed pattern noise (FPN). On the other hand, the accuracy of many computer vision algorithms, such as the extraction of local feature descriptors in images, can be sensitive to variations in the parameters of the operation. For this reason, in most cases, the function implemented is by itself a feasible approximation of the function ideally contemplated in the original design of the vision algorithm.

Taking into account that power consumption and algorithmic accuracy must be properly balanced in embedded devices, it is essential to carry out a detailed analysis of the relation between the CMOS image sensor performance and high-level computer vision tasks within the system design cycle. Overall, in this paper, we present a method which relates the performance of different computer vision feature extraction algorithms with FPN. The aim of this method is to provide electronic designers with a tool able to set the maximum value of FPN allowed to meet a given algorithm accuracy specification. Section 2 describes works related to noise modeling, 3T-APS technology and local features descriptors. In Section 3 the experimental methodology that has been used to perform the proposed analysis by means of image processing techniques is detailed. The results obtained for both binary and floating-point descriptors are discussed in Section 4. Finally we conclude in Section 5.

2. Related work

An APS is an image sensor where each picture element or pixel has a photo-detector and an active amplifier. The term active pixel sensor was coined in 1985 by Tsutomu Nakamura et al. [4] and more broadly defined by Eric Fossum [5]. The term ‘active pixel sensor’ is also used to refer to the individual pixel sensor itself, as opposed to the image sensor [6]; in that case the image sensor is sometimes called an active pixel sensor imager [7], or active-pixel image sensor [8]. There are many types of active pixel sensors, including CMOS APS used most commonly in cell phone cameras, web cameras, most digital pocket cameras since 2010, and in most digital single-lens reflex cameras (DSLRs). Such an image sensor is produced using CMOS

technology (and is hence also known as a CMOS sensor), and has emerged as an alternative to CCD image sensors.

The APS sensor amplifies the signal in each pixel by converting the charge accumulated into a gate potential. For the 3T-APS configuration in Figure 1, the transistor M_{sf} acts as a voltage follower, so that the output voltage follows the voltage of the photo-diode. The signal is transmitted to the vertical output line through the selection transistor M_{sel} . The operation of this sensor is as follows [9]: i) The reset transistor M_{rst} is set on by means of the horizontal input line RST. The photo-diode is reset to $V_{DD} - V_{th}$, where V_{th} is the threshold voltage of M_{rst} ; ii) M_{rst} is set off; iii) under an incident light source, the photo-diode accumulates photo-generated carriers in the sensing capacitor C_{int} . These carriers modify the potential in the photo-diode which decreases with respect to the intensity of the incident light, which decreases as a function of the incident light; iv) after a given t_{exp} exposure time, the selection transistor M_{sel} is activated by means of the horizontal input line ROW and the output voltage of the pixel is read on the vertical output line COL; v) once the reading process is finished, M_{sel} is deactivated and M_{rst} is activated, returning to point i).

[Figure 1 about here.]

Previous works [10, 11] have tried to evaluate the performance of hardware for software codesign modeling some physical errors. In the case of image sensors, those physical errors are mainly manifested as noise. The European Machine Vision Association (EMVA) standard 1288 [12] defines the EMVA 1288 Standard [13] in order to measure, compute and present specification parameters and characterization data for cameras and image sensors used for machine vision applications. The general assumptions covered by the standard include: i) the amount of photons collected by a pixel depends on the product of irradiance E (units W/m^2) and exposure time t_{exp} (units s), i.e., the radiative energy density Et_{exp} at the sensor plane; ii) the sensor is linear, i.e., the digital signal y increases linearly with the number of photons received; iii) all noise sources are wide-sense stationary and white with respect to time and space, i.e., the parameters describing the noise are invariant with respect to time and space; iv) only the total quantum efficiency is wavelength dependent, i.e, the effects caused by light of different wavelengths can be linearly superimposed; and v) only the dark current is temperature dependent.

102 These assumptions describe the properties of an ideal camera or sensor,
 103 as shown in Figure 2. A real sensor will depart more or less from an ideal
 104 sensor. As long as the deviation is small, the description is still valid, and it
 105 is one of the tasks of the standard to describe the degree of deviation from
 106 an ideal behaviour. In this work, it is assumed that the image pixel sensor
 107 to be simulated complies with the necessary features to be described by the
 108 mathematical pixel model proposed by the standard. This mathematical
 109 model tries to follow the physical model of an image sensor. The idea is
 110 that a digital image sensor essentially converts photons hitting the pixel area
 111 during the exposure time by a sequence of steps finally into a digital number.
 112 That sequence is as follows: a number of photons (μ_p) hitting the pixel area
 113 during exposure time (t_{exp}) creates a number of electrons (μ_e) determined
 114 by the quantum efficiency (η). These electrons, together with those that are
 115 product of noise and other device non-idealities (μ_d) form a charge which is
 116 converted by a capacitor to a voltage. This voltage is then amplified with
 117 a gain (K) and digitized by means an analog-digital converter (ADC) that
 118 introduces a quantization noise (σ_q). At the end of this process the result is
 119 a digital grey value (y).

120 At the highest level of abstraction for this grey digital image, a keypoint
 121 is a small portion of the image that, for any reason, is unusually distinctive,
 122 and can be easily identified in a related image. A descriptor is some math-
 123 ematical construction, typically a vector of floating-point or binary values,
 124 which somehow describes an individual keypoint, and which can be used to
 125 determine whether -in some context- two keypoints from two different images
 126 correspond to a same feature. There are roughly two categories of descriptors.
 127 On the one hand, there are floating-point descriptors based on the Histogram
 128 of Gradients (HOG), that is, SIFT [14], SURF [15], VGG [16] and Daisy [17].
 129 On the other hand, there are the binary descriptors, BRISK [18], BRIEF [19],
 130 ORB [20], LATCH [21], FREAK [22], KAZE [23], AKAZE [24], among others
 131 that have demonstrated to be successful alternatives that provide similar per-
 132 formance to their floating point counterparts while being efficient to calculate
 133 and store. In this paper, a comprehensive evaluation of the performance of
 134 cutting-edge binary descriptors, that is, BRIEF (ORB), BRISK, and those
 135 based on Histogram of Gradients such as SIFT and SURF, is presented in the
 136 context of image matching under various geometric and photometric image
 137 transformations.

138 [Figure 2 about here.]

139 3. Experimental methodology

140 Our aim is to match two complex images, containing heterogeneous ob-
141 jects that are arranged in the background, by means of a matrix of feature
142 descriptors. Each descriptor is a vector which is linked to a keypoint, and
143 each element of the vector can be a binary or a non-binary value. The image
144 is contaminated by a model of fixed pattern noise based on EMVA standard
145 1288. We want to assess how this fixed pattern noise hinders the matching
146 operation. A keypoint will be considered a true positive if the keypoint is
147 an inlier of a homography transformation between images. The outliers will
148 be considered false positives. The noise contribution of main interest for us
149 is the column-wise fixed pattern noise since it is created in CMOS imagers
150 which include column-parallel ADC readout architectures.

151 The process of matching two images consists in comparing every feature
152 in the image A to every feature in the image B, in order to detect which
153 keypoints refer to the same feature in both images. Three strategies can be
154 used if the distance is the metric used to assess the matching: brute force
155 using near neighbour distance rate (NNDR), cross checking and k-d trees
156 or hash tables. To this end, once some hypothetical or predictive matches
157 have been obtained, geometric alignment (homography transform) is used to
158 verify which matches are inliers (true positives) and which ones are outliers
159 (false positives). The followed procedure involves four stages, as shown in
160 Figure 3. Stage 1 consists of a noise model which is added to the image.
161 Stage 2 performs the extraction and description of the features of the images.
162 Stage 3 carries out a matching stage, where the images are compared using
163 the three aforementioned matching strategies. Stage 4 uses a homography
164 transformation to obtain a fit of only those features matches (inliers) that
165 are sufficiently close to this estimated transformation.

166 [Figure 3 about here.]

167 3.1. Modeling fixed pattern noise

168 The noise contribution of main interest for us is the fixed pattern noise
169 (FPN) which is the variation in output pixel values, under uniform illumi-
170 nation, due to device and interconnect mismatches across an image sensor.
171 It is fixed for a given sensor, but varies from sensor to sensor. FPN consists
172 of offset and gain components. It increases with illumination, but causes
173 more degradation in image quality at low illumination. In a CCD image

174 sensor, FPN is modeled as a sample from a spatial white noise process. A
 175 spatial white noise random process is a set of zero-mean uncorrelated ran-
 176 dom variables with the same standard deviation. If the random variables
 177 are Gaussian, the noise is completely specified by standard deviation. This
 178 white noise model is not suitable for characterizing FPN in CMOS sensors
 179 due to the strong differences of the readout circuitry used in CMOS sensors
 180 and CCDs. Both CMOS passive pixel sensor (PPS) and APS have higher
 181 FPN than CCDs and suffer from column FPN, which appears as “stripes” in
 182 the image and can result in significant image quality degradation. In CMOS
 183 image sensors, pixel transistors cause additional pixel FPN while column am-
 184 plifiers cause column FPN. As a result, FPN is in general higher in CMOS
 185 than in CCDs. Therefore, we represent FPN as the sum of two components:
 186 column-level and pixel-level.

187 Pixel-wise and column-wise FPN are mainly caused by the variation in
 188 the photodetector parameters and dark current. In APS it is mainly caused
 189 by variations in transistor parameters. Both FPN noise terms, are related
 190 with the operation of the source follower, M_{sf} , which in a first approximation
 191 provides an output voltage given by:

$$V_{out} = V_{pix} - V_{T_{sf}} - \sqrt{I_B/\beta_{sf}} \quad (1)$$

192 where V_{pix} is the pixel voltage, I_B is the column bus current and β_{SF} is
 193 the saturation transconductance factor for M_{SF} . This is the FPN term that
 194 occurs in a single pixel independently from the rest of pixels. It was shown
 195 in a seminal paper by Pelgrom et al. in 1989 [25] that, in any given MOS
 196 technology, the variance of the transistor threshold voltage V_T (threshold
 197 mismatch) among adjacent transistors reduces inversely with the gate area.
 198 This is known as Pelgrom’s law:

$$\sigma_{V_T}^2 = A_{V_T}^2/2W_{sf}L_{sf} \quad (2)$$

199 where A_{V_T} is a constant named Pelgrom’s model constant that depends only
 200 on the process, W_{sf} is SF transistor width and L_{sf} is the M_{sf} transistor
 201 length. Conversion gain (K) expresses, in volts per unit charge, how much
 202 voltage change is obtained by one electron at the charge detection node.
 203 Thus, in terms of noise contributions, it can be incorporated to the model
 204 as:

$$\sigma_{\Delta V_T}^2 = (1/K^2)A_{V_T}^2/2W_{sf}L_{sf} \quad (3)$$

For column-wise FPN, variations of the column bus current (I_B) from M_{sel} introduce an additional offset. Its contribution in electrons is:

$$\sigma_{\Delta I_Q}^2 = \frac{I_B}{4\beta_{sf}K^2} \left(\frac{A_\beta^2}{W_B L_B} + 4 \frac{\beta_B}{I_B} \frac{A_{V_T}^2}{W_B L_B} \right) \quad (4)$$

where β_B is the saturation transconductance factor for bias, W_B and L_B is the width and length from transistor bias M_{sel} , and A_β^2 is the Polgrom's model constant.

3.2. Feature descriptors

A corner is a small patch of an image that is rich in local information. A keypoint is a small patch of an image that is rich in local information which is unique. Local information is stored in the form of a descriptor, which exhibits lower dimensionality than keypoint features. The idea behind this is that descriptor is much easier to recognize, unique or nearly unique, when it appears in another different image. The earliest ancestor of the modern keypoint is the Harris corner [26] which is the predecessor of the modern keypoints as well as their descriptors. The idea of Harris corner is that there are many kinds of local features (edges, grey levels, gradients, etc) that can be detected although in practice, the point or feature to be selected should be: 1) unique, or nearly unique in order to have a good chance of finding that point again and; 2) parameterizable in order to be compared.

Harris corners are rotation-invariant, which means that even if the image is rotated, the same corners can be found. Another important property is scale invariability. But a corner may not be seen as a corner if the image is scaled, due to possible losses of some strong derivatives in the scaled patch. In 2004, David Lowe [14] proposed a new algorithm to obtain scale invariant keypoints: the Scale-Invariant Feature Transform (SIFT). Lowe introduced a new property to the SIFT features to assure that the features would be distinctive. The SIFT algorithm extracts keypoints and compute their descriptors. The procedure can be divided in two main computational operators: keypoints detector and keypoints descriptor. The SURF algorithm (Speeded-Up Robust Features) was originally proposed in 2006 by Bay et al. [15, 27]. SURF is also based on taking histograms of gradients orientation in the same way as SIFT. The algorithm can be understood as an evolution of the SIFT feature discussed just above.

237 SIFT and SURF features are notable examples of the family of Histograms
 238 of Oriented Gradients (HOG) based descriptors. Although highly discrim-
 239 inative and robust to various image transformations, HoG based features
 240 rely on computationally expensive gradient histogram pooling and results
 241 in a high dimensional feature vector of floating-point values. To decrease
 242 the dimensionality of local feature descriptors, recent works propose several
 243 approaches to design binary, not real-valued, local feature descriptors, since
 244 they require much less storage. They also enable faster matching as there
 245 are efficient indexing schemes for binary vectors and Hamming distances can
 246 be computed fast on many architectures, including mobile devices.

247 In general, binary descriptors are composed of three parts: a sampling
 248 pattern, sampling pairs and orientation compensation. Precisely, the pro-
 249 cedure or method to obtain each of these parts is different in each binary
 250 feature, as is shown in Table I. The descriptor is binary because it is com-
 251 posed out of ‘1’ and ‘0’ encoding the local information around the keypoint.
 252 Orientation compensation is obtained rotating the patch an determined angle
 253 and extracting a binary string describing the rotated patch. Both strings are
 254 no similar but the pairs remained the same. That ensures that the description
 255 is rotation invariant.

256 [Table 1 about here.]

257 Thanks to all these properties, binary descriptors are perfect candidates
 258 for real-time applications. BRIEF [28] uses random pre-determined locations,
 259 whereas BRISK [29] uses an exhaustive set of comparisons of close locations.
 260 ORB [30] relies on optimization and aims at improving the recognition rates
 261 by choosing the locations that decorrelate the tests. Similarly, FREAK [22]
 262 selects the intensity tests that provide the highest bit variance. Thanks to the
 263 simplicity of the above mentioned binary descriptors, they quickly attracted
 264 a lot of attention in the Computer Vision community and have become a
 265 very popular element of many real-time applications.

266 3.3. Matching methods and strategies

267 Once the features and their descriptors have been extracted from two
 268 or more images, they must be matched each other, i.e., all features in the
 269 image A are compared to all of the features in the image B in order to deter-
 270 mine which corresponding locations in different images are the same feature.
 271 This strategy is the most basic and obvious choice and is called brute force

272 matching. The feature descriptors can directly use Euclidean distances for
 273 descriptors represent the histogram of oriented gradient or the Hamming dis-
 274 tance for binary descriptors, in feature space for ranking potential matches.
 275 For a Euclidean or Hamming distance give as metric, the simplest matching
 276 strategy is to set a threshold, i.e., maximum distance of similarity, and to
 277 return all matches from other images within this threshold. Too many false
 278 positives will be generated if the threshold is too high, i.e., incorrect matches
 279 will be returned. Too many false negatives will be generated if the threshold
 280 is too low, i.e., too many correct matches will be missed. A better strategy
 281 for this kind of brute-force method could be match the nearest neighbor in
 282 a cross check way too. A good match (fa, fb) is obtained for images Ia
 283 and Ib if feature fb is the best match for fa in Ib and feature fa is the best
 284 match for fb in Ia . In this way the matching only conserves the bidirectional
 285 matches and ideally the strongest correspondence has been kept. Ideally, this
 286 threshold itself will adapt to different regions of the feature space but requires
 287 additional time to calculate.

288 A second heuristic strategy can be to compare the nearest neighbor dis-
 289 tance to that of the second nearest neighbor [31]. In order to filter the
 290 matches, Lowe [14] proposed to use a distance ratio test to try to eliminate
 291 false matches. The distance ratio between the two nearest matches of a con-
 292 sidered keypoint is computed and it is a good match when this value is below
 293 a threshold. Indeed, this ratio allows helping to discriminate between am-
 294 biguous matches (distance ratio between the two nearest neighbors is close
 295 to one) and well discriminated matches. This nearest neighbor distance ratio
 296 can be defined as follows:

$$\text{NNDR} = \frac{d_1}{d_2} = \frac{\|D_A - D_B\|}{\|D_A - D_C\|}$$

297 where d_1 and d_2 are the nearest and second nearest neighbor distances, D_A
 298 is the target descriptor, and D_B and D_C are its closest two neighbors

299 So far, the simplest strategy to find all corresponding feature points is to
 300 match all features against all other features in each pair of images. Unfor-
 301 tunately, this brute force strategy is quadratic in the number of extracted
 302 features, which makes it impractical for most applications. A better strategy
 303 is to devise an indexing structure, such as a multi-dimensional search tree
 304 or a hash table, to rapidly search for features near a given feature. Multi-
 305 index hashing is a strategy [32] where, given a dataset populated with binary
 306 codes, each code is indexed m times into m different hash tables, according

307 to m adjacent substrings it has been divided into. Thus, given a query code,
 308 all the entries close to it at least in one substring are returned by search
 309 as neighbor candidates. Returned entries are then checked for validity by
 310 verifying that their full codes are not distant (in Hamming space) more than
 311 r bits from query code. Another widely used class of indexing structures
 312 are multi-dimensional search trees. The best known of these are k-d trees,
 313 or kd-trees, which divide the multi-dimensional feature space along alternat-
 314 ing axis-aligned hyperplanes, choosing the threshold along each axis so as
 315 to maximize some criterion, such as the search tree balance. The k-d tree
 316 recursively splits this plane along axis-aligned (horizontal or vertical) cutting
 317 planes. The splits are arranged so as to try to balance the tree, i.e., to keep
 318 its maximum depth as small as possible. Table II summarizes the method,
 319 strategy, norm used for matching, number of neighbours calculated and cri-
 320 terium of distance for all descriptors (HoGs based and binaries) used in this
 321 paper.

322 3.4. Homography transformation

323 Once some hypothetical (putative) matches have been obtained, geomet-
 324 ric alignment can be used to verify which matches are inliers and which ones
 325 are outliers. A global geometric transform called homography can be fitted
 326 keeping only those feature matches (inliers) that are sufficiently close to this
 327 estimated transformation. It is possible to express this transformation in
 328 terms of matrix multiplication if we use homogeneous coordinates to express
 329 both the viewed point $\vec{Q}$ and the point $\vec{q}$ on the imager to which $\vec{Q}$ is mapped
 330 then we can express the action of the homography simply as $\vec{q} = s \cdot H \cdot \vec{Q}$,
 331 where the parameter s is a scale factor and H is a 3×3 matrix called homog-
 332 raphy matrix. The homography matrix H relates the positions of the points
 333 on a source image plane to the points on the destination image plane.

334 The process of selecting a small set of seed matches and then verifying a
 335 larger set is often called random sample consensus or RANSAC [33]. In the
 336 RANSAC method, subsets of the provided points are selected at random, and
 337 a homography matrix is computed for just that subset. It is then refined by
 338 all of the remaining data points that are roughly consistent with that initial
 339 estimation. The inliers are those that are consistent, while the outliers are
 340 those that are not. The RANSAC algorithm computes many such random
 341 samplings, and keeps the one that has the largest portion of inliers. This
 342 method is extremely efficient in practice for rejecting noisy outlier data and
 343 finding the correct answer.

344

[Table 2 about here.]

345 **4. Results and discussion**

346 As an illustration of the possibilities of incorporating hardware non-
 347 idealities to the evaluation of the algorithm performance, we have chosen to
 348 test the influence of pixel-wise (pw) and column-wise FPN on the precision
 349 and recall rates of the matching for binary and non-binary local descriptors,
 350 specific SIFT, SURF, BRISK and ORB descriptors. As it will be explained
 351 below, precision is the fraction of true positive detections from all objects
 352 detected—including false positives—and recall is the fraction of true posi-
 353 tive detections from all the relevant objects (keypoints) in the dataset, were
 354 they detected or not.

355 The images employed to test the algorithm have been taken from the
 356 Mikolajczyk benchmark [34] which is a publicly available and standard bench-
 357 mark for evaluating local descriptors. The benchmark consists of 8 image
 358 sets, each containing 6 images that depict an increasing degree of a cer-
 359 tain image transformation: i) Bark – zoom + rotation changes; ii) Bikes –
 360 blur changes; iii) Boat – zoom + rotation changes; iv) Graffiti – view point
 361 changes; v) Leuven – illumination changes; vi) Trees – blur changes; vii) UBC
 362 – JPEG compression; viii) Wall – view point changes. This study has been
 363 focused on view point and rotation changes. Therefore the databases used
 364 have been the following: Bark, Boat, Graffiti and Wall. The matching score
 365 is computed on the test data, which is a set of images with a gradually in-
 366 creasing transformation between the reference frame and the other images.
 367 For example, for images sequence with viewpoint change, each image is ro-
 368 tated in 20 degrees with reference to the previous image. The ground truth is
 369 a homography that projects points to the reference frame. Figure 4 displays
 370 an example of an image of the dataset affected by growing values of both
 371 pixel-wise and column-wise FPN.

372

[Figure 4 about here.]

373 Fawcett [35] points that the performance of a matching algorithm at a par-
 374 ticular threshold can be quantified by first counting the number of true and
 375 false matches and match failures, using the following definitions: predicted
 376 matches correctly detected (T_p = true positives); predicted no-matches in-
 377 correctly detected (F_n = false negatives); predicted matches incorrectly de-
 378 tected (F_p = false positives); predicted no-matches correctly detected (T_n =

379 true negatives) and then these numbers can be converted into unit rates: pre-
380 dicted matches ($P' = T_p + F_p$); predicted non-matches ($N' = F_n + T_n$); true
381 matches ($P = T_p + F_n$); true non-matches ($N = F_p + T_n$); true positive rate or
382 recall ($TPR = T_p/P$); false positive rate ($FPR = F_p/N$); positive predictive
383 value or precision ($PPV = T_p/P'$); accuracy ($ACC = (T_p + T_n)/(P + N)$).
384 Figure 5 shows as sample the matching of SIFT, SURF, ORB and BRISK
385 descriptors computed between the reference frame and an image with a view-
386 point change of 40 degrees.

387 [Figure 5 about here.]

388 Figure 6 shows a sample confusion matrix or contingency table containing
389 such numbers for a matching procedure based on cross checking and SIFT
390 descriptor between the image one (or reference frame) and the image two
391 (viewpoint 20°) in the database Graffiti with 0% of fixed pattern noise in both
392 images. The matrix shows the number of true positives (TP), false positives
393 (FP), false negatives (FN) and true negatives (TN). The columns sum up to
394 the actual number of positives (P) and negatives (N), while the rows sum
395 up to the predicted number of positives (P') and negatives (N'). Besides, the
396 positive predictive value (PPV) or precision, the negative predictive value
397 (NPV), sensitivity or recall (class) or true positive rate (TPR), the false
398 positive rate (FPR), the false negative rate (FNR), the specificity or true
399 negative rate (TNR), and the accuracy (ACC) are shown.

400 [Figure 6 about here.]

401 The ideal system corresponds to precision and recall equal to one. In
402 practice, a compromise between these two quantities exists: a system with a
403 high recall is likely to have false positives, and a system with high precision
404 is likely to miss some true annotations. Often, the two quantities are sum-
405 marized into a single number, F , defined as the harmonic mean of precision
406 (P) and recall (R): $F = 2PR/P + R$. The value of F measures the accuracy
407 of a test that presents a binary classification, weighting precision (P) and
408 completeness or recall (R). Take values from 0 to 1 with 1 being the best
409 possible case and 0 the worst case. The harmonic mean between precision
410 and recall has been considered, known as traditional F-Measure or balanced
411 F1Score.

412 The consequences of applying different values for the mismatch in the
413 threshold of the pixels' source follower, which results in a pw-FPN, and the

columns' bias current, that results in a cw-FPN, can be seen in Figures 7, 8, 9 and 10; and Figures 11, 12, 13 and 14, respectively. Therefore, cw-FPN is varied for a fixed value of the pw-FPN in Figures 7 to 10 and, and the other way around in Figures 11 to 14. Within each graph, each line corresponds to a F1Score for a descriptor, a method of matching and a change of viewpoint against a percent of noise—which ranges from 0% to 100% in steps of 5%—. The figures below show the matching score of different detectors measured across viewpoint angle. Each point on a curve is the matching score computed between the reference frame and image with a viewpoint change with a percent of PFN noise.

Observing the graphs, it can be clearly seen that the databases contaminated with cw-FPN undergoing only a change of viewpoint have a higher F1Score and decay with a lower slope than those databases that also have zoom. From these previous databases, it can be seen that between 40 and 60% of the cw-PFN noise, F1Score has a value of 0 for all descriptors and matching methods. Obviously it can also be observed that, as the angle changing the view and zoom is greater between the reference image and the rest of the images, the F1Score is smaller. It also seems that the FLANN and brute force methods work better with low noise whereas the cross checking method works better with high noise level.

[Figure 7 about here.]

[Figure 8 about here.]

[Figure 9 about here.]

[Figure 10 about here.]

[Figure 11 about here.]

[Figure 12 about here.]

[Figure 13 about here.]

[Figure 14 about here.]

442 It can be seen that for a zero fixed value of cw-FPN, by increasing the
 443 value of pw-FPN —what can be seen in Figure 11 to Figure 14 plots—, the
 444 degradation of F1Score is much weaker than the variation obtained by fixing
 445 pw-FPN to zero and increasing cw-FPN —which is depicted in Figure 7 to
 446 Figure 10 plots. It can be concluded that cw-FPN has a stronger deterior-
 447 ating effect in the object detection algorithm than pw-FPN has. This is
 448 specially important in CMOS imagers which include column-parallel ADC
 449 readout architectures. Therefore, given a feature extraction algorithm and
 450 a specified accuracy, these graphs provide a method to define the maximum
 451 cw-FPN allowed when designing the CMOS ADC. This allows to relax the
 452 ADC specifications in order to find a balance between circuit power dissipa-
 453 tion and algorithm accuracy.

454 Equivalently, from the point of view of the algorithm, a new cascade
 455 of classifiers could be trained to cope with the artifacts caused by a large
 456 cw-FPN. Either way, the influence of hardware non-idealities are evidenced
 457 with this methodology, allowing comprehensive optimization and co-design
 458 of image sensor hardware and algorithm parameters.

459 5. Conclusions and future work

460 The design of an embedded vision system cannot always be achieved
 461 through a traditional top-down approach. Optimization at different levels is
 462 necessary. Thus, it is possible to work at algorithm levels and incorporate a
 463 low level description of the non-idealities of the image sensor to evaluate its
 464 influence on the performance of the vision algorithm. A feasible way to do
 465 this is to incorporate the necessary models that allows to evaluate the effect
 466 of the deviation of the physical parameters of the sensor with the performance
 467 of the artificial vision algorithms and their implementation. This has been
 468 done in this work. The main advantage is that these models are well known
 469 by the community of vision application developers. The co-design of vision
 470 hardware and software is possible in this way. As an example, we have
 471 shown the effect of pw- and cw-FPN in the detection and description of local
 472 features.

473 Nonetheless, there is much scope for extension. In particular, a more
 474 sophisticated means of obtaining the number of matches correctly and incor-
 475 rectly estimated by a feature matching algorithm is desirable. This would
 476 likely require more fundamental research in the field. On the other hand,
 477 the complete imaging methodology could be enhanced by also incorporating

other design effects (i.e., optical design). Nevertheless, the study in this direction is beyond the scope of this paper and left for the subject of our next comparison.

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	Sampling pattern	Orientation calculation	Sampling pairs
BRIEF	None.	None.	Random.
ORB	None.	Moments.	Learned pairs.
BRISK	Concentric circles with more points on outer rings.	Comparing gradients of long pairs.	Using only short pairs.
FREAK	Overlapping concentric circles with more points on inner rings.	Comparing gradients of preselected 45 pairs.	Learned pairs.

Table I: Method elected for each part of a binary descriptor

Method	Strategy	Descriptor	Norm	K	Threshold
Brute Force	Cross Checking	Binary	Hamming	1	$4 \times \text{min. distance.}$
		non-Binary	Euclidean	1	$4 \times \text{min. distance.}$
FLANN	KNN	Binary	Hamming	2	NNDR = 0.78
		non-Binary	Euclidean	2	NNDR = 0.78
	LSH	In-Binary	Hamming	2	NNDR = 0.78
	K-D Tree/KNN	non-Binary	Euclidean	2	NNDR = 0.78

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Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

	True Matches	True non-Matches	
Pred. Matches	$T_p = 995$	$F_p = 156$	$P' = 1151$
Pred. non-Matches	$F_n = 1802$	$T_n = 2099$	$N' = 3901$
	$P = 2797$	$N = 2255$	$T = 5052$
	$TPR = 0.3557$	$TNR = 0.9433$	$ACC = 0.6124$
	$FNR = 0.6443$	$FPR = 0.0567$	

Figure 6

Figure 11

Figure 12

Figure 13