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# 1 Palmprint and face score level fusion: hardware 2 implementation of a contactless small sample 3 biometric system

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**Abstract.** Including multiple sources of information in personal identity recognition and verification gives the opportunity to greatly improve performance. We propose a contactless biometric system that combines two modalities: palmprint and face. Hardware implementations are proposed on the Texas Instrument Digital Signal Processor and Xilinx Field-Programmable Gate Array (FPGA) platforms. The algorithmic chain consists of a preprocessing (which includes palm extraction from hand images), Gabor feature extraction, comparison by Hamming distance, and score fusion. Fusion possibilities are discussed and tested first using a bimodal database of 130 subjects that we designed (uB database), and then two common public biometric databases (AR for face and PolyU for palmprint). High performance has been obtained for recognition and verification purpose: a recognition rate of 97.49% with AR-PolyU database and an equal error rate of 1.10% on the uB database using only two training samples per subject have been obtained. Hardware results demonstrate that preprocessing can easily be performed during the acquisition phase, and multimodal biometric recognition can be treated almost instantly (0.4 ms on FPGA). We show the feasibility of a robust and efficient multimodal hardware biometric system that offers several advantages, such as user-friendliness and flexibility. © 2011 Society of Photo-Optical Instrumentation Engineers. [DOI: 10.1117/1.3534199]

Subject terms: multimodal biometrics; face recognition; contactless palmprint recognition; small-number sample sets; palm codes; score fusion; hardware implementation.

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## 30 1 Introduction

31 Biometrics has drawn extensive attention during the past 30  
32 years for its huge potential in many applications, such as  
33 building/store access control, suspect identification, surveil-  
34 lance, and human computer interfacing. The key issue of  
35 these applications is the identification of individuals by their  
36 physiological or behavioral characteristics (e.g., face, finger-  
37 print, iris, signature, or gait). Each biometric characteristic  
38 has its own strengths and weaknesses: unimodal biometric  
39 systems have to contend with a variety of problems, such  
40 as noisy data, nonuniversality, spoof attacks, and unaccept-  
41 able error rates. In the past few years, researchers have more  
42 and more focused on the possibility of including multiple  
43 sources of information. Such systems, known as multimodal  
44 biometric systems, are more reliable.<sup>1</sup>

45 In many real-world applications, the number of available  
46 training samples is small, especially in the case of large-  
47 scale biometric systems. Typically, for the face recognition  
48 problem in identity documents, the number of images from  
49 each class is considerably limited: only one or two faces  
50 can be acquired from each person. Moreover, systems us-  
51 ing less training samples have a shorter enrollment stage  
52 and are more pleasant for users. A small number sam-  
53 ple sizes allows us to use little memory. Nevertheless, in  
54 the small-number sample context, many statistical methods

show poor generalization ability and degrade the classifica- 55  
tion performance.<sup>2</sup> In this paper, a reliable and contactless 56  
general-public multimodal biometric system is presented. It 57  
respects the small-number sample constraint and tries to be 58  
user-friendly. 59

Palmprint can be used as a reliable human identifier be- 60  
cause the pattern of ridges is unique and their details are 61  
permanent. Compared to other physical biometric charac- 62  
teristics, palmprint biometrics have several advantages: low- 63  
intrusiveness, stable line features, and low-cost capturing 64  
device.<sup>3</sup> Although palmprint is traditionally a contacting bio- 65  
metric, we use it without contact, which allows us to keep 66  
a pleasant and hygienic system. For that matter, an increas- 67  
ing number of works have interest in the use of contactless 68  
sensors.<sup>3-5</sup> 69

Face is one of the most studied and commercialized bio- 70  
metrics. It is well accepted because humans routinely use 71  
facial information to recognize each other. But it suffers 72  
from some weaknesses: it is particularly affected by pose, 73  
expression, or illumination. In the past decades, a lot of face 74  
recognition algorithms have been proposed: statistical anal- 75  
ysis as principal component analysis (PCA), independent 76  
component analysis (ICA), or linear discriminant analysis 77  
(LDA);<sup>6</sup> neural networks;<sup>7</sup> graph matching;<sup>8</sup> etc. 78

Fusion of face and palmprint is studied because it 79  
allows are to greatly improve performance while keeping 80  
a user-friendly and well-accepted system. Kumar and 81  
Zhang<sup>9</sup> proposed a personal verification method combining 82

83 palmprint, face, and claimed user identity to increase  
 84 authentication performance: a feed-forward neural network  
 85 is used to integrate individual matching scores and generate a  
 86 combined decision score. Jing et al.<sup>6</sup> use face and palmprint  
 87 for small-number sample recognition: the fusion occurred  
 88 at the pixel level on feature images is obtained due to  
 89 a Gabor filter bank. Zhang et al.<sup>10</sup> present a geometry  
 90 preserving projection (GPP) approach to preserve the  
 91 interactions between the different modalities during the  
 92 subspace selection procedure: with GPP, all raw biometric  
 93 data (face, palmprint obtained with contact, and gait) from  
 94 the different identities and modalities are projected onto a  
 95 unified subspace, on which classification is performed.

96 However, none of those methods are adapted to the  
 97 calculation cost or memory constraints of embedded systems.  
 98 Biometric algorithms work on raw and uncompressed  
 99 images, whose processing requires a large number of operations.  
 100 However, most of these operations are independent and can  
 101 be performed on different parts of the image at the same time.  
 102 Because of this possibility of reaching a high parallelism degree,  
 103 biometric algorithms are the right candidates for hardware  
 104 implementation. For example, some research has been conducted  
 105 in order to reduce the calculation time of monomodal biometric  
 106 systems: Yang and Paindavoine<sup>11</sup> have implemented a face-detection  
 107 and recognition algorithm—based on radial basis function  
 108 (RBF) neural network—on field-programmable gate array  
 109 (FPGA), digital signal processor (DSP), and zero instruction  
 110 set computer (ZISC) chips in order to compare the execution  
 111 times. Lopez-Ongil et al.<sup>12</sup> present the FPGA implementation  
 112 of an authentication system based on hand geometry,  
 113 which uses the continuous hamming distance to compare  
 114 hand dimension vectors. Other works explore multimodal  
 115 biometrics: Yoo et al.<sup>13</sup> have developed two DSP systems  
 116 for iris-fingerprint and face-fingerprint recognition. In their  
 117 system, the most consuming tasks are implemented on  
 118 FPGA in order to increase the system speed.

119 The aim of our project is to build a reliable general-public  
 120 biometric system, that respects multiple constraints: hygienic,  
 121 low-cost, straightforwardness, user-friendliness, real-time  
 122 processing, limited memory, small sample set, etc. The  
 123 developed system could be used in businesses, hospitals, or  
 124 schools to control door opening, record hours worked by  
 125 employees, restrict access to sensitive areas, control access  
 126 to school canteens, etc. Therefore, we present the hardware  
 127 architecture of a multimodal biometric recognition system  
 128 with massive exploitation of the inherent parallelism. Implementations  
 129 are simulated on a Texas Instrument Digital Signal Processor  
 130 (DSP) and Xilinx Field Programmable Gate Array (FPGA)  
 131 platforms. DSPs are widespread processors that are optimized  
 132 to signal processing, whereas FPGAs are inexpensive devices  
 133 adapted to parallel calculation that give the ability to quickly  
 134 create a rapid and fully functional prototype that can emulate  
 135 and verify solutions or even be embedded into the final system.  
 136 That is why we chose to implement our algorithm on these two  
 137 devices. The remainder of the paper is organized as follows:  
 138 Section 2 provides details of the algorithm model from image  
 139 acquisition to the steps of fusion and decision, while Sec. 3  
 140 presents designed architectures and their hardware implementations.  
 141 Performance of the system is presented in Sec. 4 and discussed  
 142 in Sec. 5. This is followed by the conclusion and presentation  
 143 of the perspectives in Sec. 6.

## 2 Algorithm Model 146

147 This section introduces the complete face and hand processing  
 148 chain, which includes four principal steps: acquisition of  
 149 images, hand preprocessing, palmprint and face feature  
 150 extraction, and score fusion. A brief algorithm-oriented  
 151 presentation of all the modules is available in Ref. 14.

### 2.1 Acquisition of Images 152

153 Traditional hand-based biometrics use contact with a surface  
 154 and sometimes rigid placement guides. These have the advantage  
 155 of having a fixed focal field, and if they use pegs, can rely  
 156 on a standard placement. On the contrary, face is a typical  
 157 contactless biometric. We have designed a user-friendly  
 158 system to acquire real-time hand and face images that is  
 159 totally contactless. Two low-cost Logitech QuickCam Pro  
 160 9000 USB cameras are used with a maximum resolution of  
 161  $1600 \times 1200$  to capture images under typical office lighting  
 162 and daylight conditions.

163 Subjects enroll themselves thanks to an easily usable software.  
 164 For the hand, they are only asked to place it horizontally  
 165 and ensure that their fingers do not touch each other. Each  
 166 subject could place his hand anywhere from a few dozen  
 167 inches to a few inches from the sensor: the upper limit is  
 168 defined by the position of a green background [see Fig. 1(a)].  
 169 Subjects must furthermore place their face in an enclosing  
 170 frame of  $360 \times 480$  pixels drawn on the webcam preview [see  
 171 Fig. 1(b)]. Expression, accessories, and background are not  
 172 controlled: expression can vary from neutral to broad grin,  
 173 and subjects choose to wear their eyeglasses or not.

### 2.2 Image Preprocessing 174

175 Working on palmprint in a contactless context requires some  
 176 preprocessing. The region of interest (ROI) must indeed be  
 177 extracted from the hand image. Palm extraction requires hand  
 178 localization, followed by palm localization in the hand, and

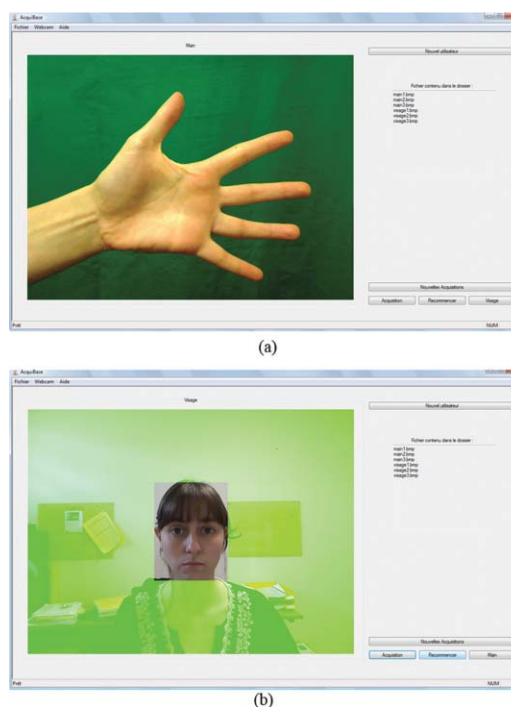


Fig. 1 Acquisition software: (a) palm interface and (b) face interface.

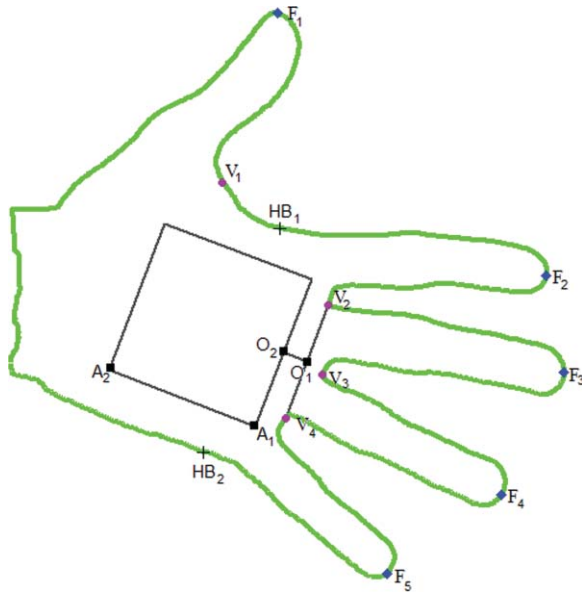


Fig. 2 Palm window definition.

179 then normalization because of the rotation and scale variation  
 180 induced by the free placement. Hand segmentation consists  
 181 of a thresholding on the red component of the RGB space:  
 182 because a green background has been chosen, the redder  
 183 pixels belong to the hand. Some morphological operations  
 184 are also used in order to enhance the hand edges. After this  
 185 step, multiple reference points are defined; they correspond to  
 186 the fingertips and valleys between fingers. This localization  
 187 of the hand extremities is achieved in two steps.

188 First, a contour extraction is performed using an eight-  
 189 neighborhood-borders tracking algorithm known as the  
 190 Freeman algorithm. Second, hand extremities's locations are  
 191 found. As subject fingers are located on the right of the im-  
 192 age, local minima and maxima of the hand contour abscissa  
 193 can be considered as fingertips and valleys. Because these  
 194 initialized locations are not accurate, we applied a refining  
 195 algorithm inspired by the method described in Ref. 5, which  
 196 minimizes the euclidean distance between the considered  
 197 point and its two neighbors among the reference points.

198 Doublet et al.<sup>4</sup> propose a simple and efficient method  
 199 to extract the palm from the location of such characteristic  
 200 points. Our adaptation of this process consists of two steps:  
 201 First, adding two characteristic points in order to calculate  
 202 the hand width, and second localizing the palm window cor-  
 203 ners. Location of the new fiducial points is deduced from  
 204 the length of the index and little fingers. Figure 2 shows the  
 205 square window, which corresponds to the ROI. The distances  
 206  $\|O_1O_2\|$  and  $\|A_1A_2\|$  depend on the distance between the  
 207 hand and the camera. Therefore, they are taken proportional  
 208 to the hand width ( $\|HB_1HB_2\|$ ).

209 Because the palmprint images are of different sizes and  
 210 orientations, we normalize them. First, they are rotated  
 211 around the vertical axis. Then, they are resized to a standard  
 212 image size of  $64 \times 64$  pixels and converted into a gray-level  
 213 image.

214 Because of the experimental setup, the pose of the face  
 215 varies only slightly. Moreover, as we work on low-resolution  
 216 images, it is not necessary to extract ROI. That is why the  
 217 face preprocessing only takes up the last palm preprocessing

218 steps: resizing to  $64 \times 64$  pixels and conversion into a gray-  
 219 level image.

### 2.3 Gabor Feature Extraction

220 Palmprints exhibit a rich pattern of striations that enable dis-  
 221 criminating between people. Therefore, most of the studies  
 222 in palmprint recognition treat palmprints as textured images  
 223 and apply well-known pattern recognition techniques, such  
 224 as wavelets,<sup>15</sup> PCA or ICA,<sup>16</sup> and many others. Because of  
 225 its good performance and specific qualities of luminosity ro-  
 226 bustness and frequency location, the Gabor filter is the most  
 227 efficient and popular tool.<sup>1,6,17</sup>

228 Face recognition is a mature biometric for which many  
 229 recognition approaches exist. Nevertheless, classical meth-  
 230 ods such as Eigenface or Fisherface are not adapted to the  
 231 small sample set problem, as explained in Ref. 2 or 18.  
 232 Therefore, many variants of these algorithms have been  
 233 proposed in order to improve recognition performance in  
 234 this situation.<sup>19,20</sup> Other methods, which combine image fil-  
 235 tering by a Gabor filter bank and PCA (Ref. 6) or LDA  
 236 (Ref. 21) have also been studied to solve the small-number  
 237 sample set problem. However, all these methods based on  
 238 statistical analysis require too high calculation complexity  
 239 and too much memory to be used in embedded systems.  
 240 However, some studies look into the use of one or more per-  
 241 tinent Gabor filters,<sup>22,23</sup> which is the same principle as our  
 242 palmprint recognition algorithm.

243 Here, this filter is used to extract palmprint and face fea-  
 244 tures: a coding-based method is employed, that is founded  
 245 on the works of Refs. 4 and 24. This choice is also consis-  
 246 tent with the electronic embedded system context: regular  
 247 calculations, such as convolution operation, are easily imple-  
 248 mented on hardware systems and reduce power consumption.  
 249 Moreover, applying the same method on both palmprint and  
 250 face will facilitate hardware implementations.

251 A variety of implementations of this filter exists. Consid-  
 252 ering its performance and the need to reduce computation  
 253 time and memory consumption, we use the ellipsoidal filter  
 254 in the real domain proposed in Ref. 4,  
 255

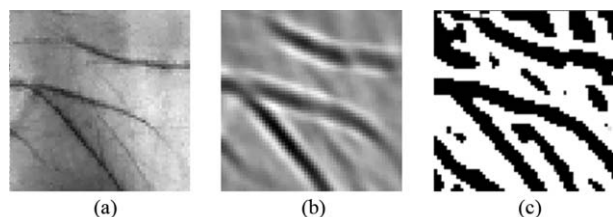
$$G(x, y) = \exp \left[ -\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2} \right] \cos \left( 2\pi \frac{0.56x'}{\sigma} \right), \quad (1)$$

256 where

$$\begin{cases} x' = (x - x_0) \cos(\Theta) - (y - y_0) \sin(\Theta) \\ y' = (x - x_0) \sin(\Theta) + (y - y_0) \cos(\Theta) \end{cases} \quad (2)$$

257 The couple  $(x_0, y_0)$  defines the function center,  $\Theta$  controls the  
 258 orientation,  $\sigma$  is the standard deviation of the Gaussian factor,  
 259 and  $\gamma$  is the spatial aspect ratio of this ellipsoidal function  
 260 fixed at 0.5. For more luminosity robustness, the filter is  
 261 normalized by the subtraction of the coefficient average from  
 262 each coefficient.

263 Gabor palmprint features are obtained by the convolution  
 264 of the image with a single Gabor filter (whose coefficients  
 265 are empirically chosen, see Sec. 5), followed by a thresh-  
 266 olding operation with a threshold equal to 0. This binariza-  
 267 tion limits the characteristic size and the computation time in  
 268 the comparison phase. The feature extraction step is illustrat-  
 269 ed in Fig. 3. For identity classification and verification, a sim-  
 270 ilarity measurement must be created in order to compare  
 271 the extracted parameters. For this matching process, we use  
 272 the traditional comparison method of binary matrices: the



**Fig. 3** Feature extraction of the palm: (a) corresponding images, (b) gabor features ( $\Theta = \pi/4, \sigma = 4.6$ ), and (c) final feature matrix.

Hamming distance, which is a pixel-by-pixel comparison using the Boolean operator  $\oplus$  (XOR).

Because palmprint and face localizations are not necessarily ideal, we introduce a tolerance in translation by calculating the distance for multiple shifts and taking the minimum. The final matching measurement for two feature matrices  $A$  and  $B$  of size  $N \times N$  is

$$D(A, B) = \min_{|x|, |y| < 2} \left[ \sum_{i=0}^N \sum_{j=0}^N T\{A(i, j), x, y\} \oplus B(i, j) \right], \quad (3)$$

where  $T\{A, x, y\}$  is the translation of image  $A$  horizontally by  $x$  and vertically by  $y$ .

### 2.4 Fusion Scheme

Combining one or more biometric traits provides new independent information that gives the opportunity to greatly improve recognition performance. Furthermore, it increases the probability that one of the traits suits the user, which gives a larger population coverage and complicates spoof attacks by requiring more kinds of information.

A generic biometric system includes four principal steps: data acquisition, feature extraction, matching to the template database, and decision. Information fusion can occur at any of the aforementioned steps. Most studies agree on the fact that integrating information at an early stage of processing is more effective than performing integration at a later stage.<sup>1</sup> Earlier stages contain richer information about the input biometric data than later stages. However, fusing pixels or feature

vectors implies a high compatibility between fused data and does not allow modality-adapted processing, as in our case.

We use fusion at score level because there is sufficient information content at this step and it is easy to access and combine the matching scores. Savic and Pavesic<sup>25</sup> have demonstrated that the combination approach performs better in biometric systems. Therefore, tree combination rules have been tested. Let  $P_i$  be the score obtained thanks to the matching between the current palmprint feature and the  $i$ th template of the palmprint matching base, let  $F_i$  be the score obtained thanks to the matching between the current face feature and the  $i$ th face template, the corresponding final score  $Fus_i$  can be calculated from the minimum [Eq. (4)], the sum [Eq. (5)], and the multiplication Eq. (6) rules as follows:

$$Fus_i = \min(P_i, F_i), \quad (4)$$

$$Fus_i = P_i + F_i, \quad (5)$$

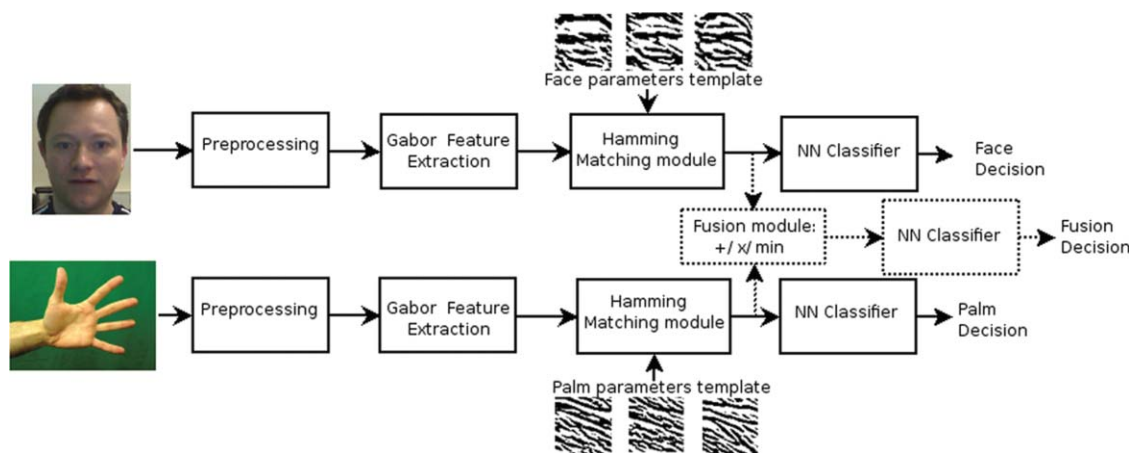
$$Fus_i = P_i \times F_i. \quad (6)$$

The final decision of the classifier is then given by choosing the class that minimizes the fused matching measures between the sample and all templates of the matching base.

If at least one of the two scores is low enough to success in the recognition task, the fused score (obtained by minimum, sum, or multiplication rules) would also allow one to succeed in this task. That is why multimodal systems outperform unimodal systems and increase the population coverage: If one modality is vulnerable to certain conditions, then the others take over. The way we designed the system (see Fig. 4) allows us, moreover, to use palmprint only, face only, or fusion of the two. Using this architecture makes it possible to add other textured modalities, such as knuckleprint or ear.

### 3 Hardware Implementations

Each of the proposed algorithms respects the embedded system constraints. They work in particular with a low calculation cost and low memory, which makes them particularly suitable for DSP implementation. Moreover the coding scheme proposes a high potential of parallelization, which could be fully exploited by application-specific integrated



**Fig. 4** Entire processing chain with possible score fusion using nearest-neighbor (NN) classifier.

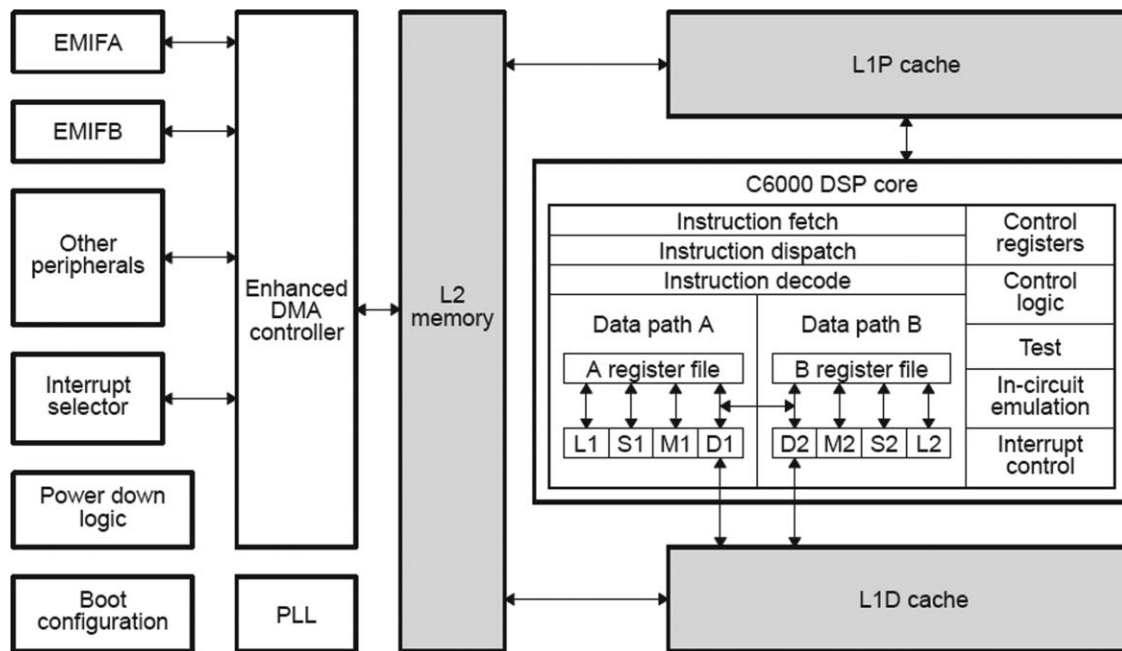


Fig. 5 TMS320C64x DSP block diagram.

334 circuit (ASIC) or FPGA. We propose the implementation of  
 335 the entire system on a Texas Instrument DSP platform, and  
 336 the implementation of the multimodal recognition step on a  
 337 Xilinx FPGA platform. Implementing the proposed multi-  
 338 modal recognition chain in FPGA efficiently is the key step  
 339 of an ASIC solution design.

### 340 3.1 DSP Implementation

341 The implementation of the processing chain has been  
 342 simulated on a TMS320C64xx DSP platform of Texas  
 343 Instruments<sup>26</sup> thanks to the Code Composer Studio (CC-  
 344 Studio) tool. Such platforms are particularly well adapted to  
 345 classical image processing algorithms, and allow one, at the  
 346 same time, to easily implement more sophisticated process-  
 347 ing. The C64x central processing unit (CPU), as shown in  
 348 Fig. 5, consists of eight functional units, two register files,  
 349 and two data paths. Devices of the c64x family can execute,  
 350 for example, four 16-bit×16-bit multiplies every cycle, or  
 351 eight 8-bit×8-bit multiplies. They have a two-level memory  
 352 architecture for program and data. The first-level program  
 353 cache is designated L1P on Fig. 5, and the first-level data  
 354 cache is designated L1D. Both the program and data mem-  
 355 ory share the second-level memory, designated as L2, which  
 356 is configurable and can provide up to 1024 KB of on-chip  
 357 SRAM. A DSP implementation description has been made  
 358 in C language. After an optimization step, we let the com-  
 359 piler of the CCStudio environment decide the possibilities of  
 360 parallelization.

361 The number of CPU cycles required for the palmprint  
 362 extraction depends of the hand shape. Our simulations em-  
 363 pirically show that it is between  $350 \times 10^6$  and  $390 \times 10^6$ ,  
 364 which corresponds to 350 and 390 ms at a frequency of  
 365 1 GHz. With such a short execution time, palmprint extrac-  
 366 tion can be performed during face image acquisition. The face  
 367 preprocessing always uses the same number of CPU cycles,  
 368 which is lower than  $6 \times 10^6$  and corresponds to an execution

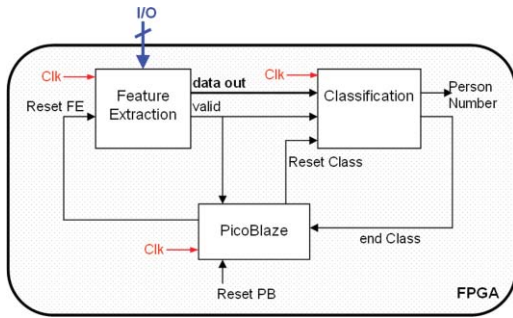
time of 6 ms. Face preprocessing could run in real time while  
 storing pixels. For these first hardware implementations, we  
 have chosen to work on a database of 25 people with two  
 samples per individual in the matching base. Guided by the  
 results of our algorithmic model (see Sec. 4 or Ref. 14), we  
 have chosen to perform the fusion thanks to the sum rule.  
 As feature samples are  $52 \times 52$  binary matrices, the total size  
 of the base is only of 16 KB. The coding scheme and the  
 recognition step requires about  $7 \times 10^6$  CPU cycles, which  
 corresponds to 7 ms.

Although parallelization possibilities are high for this kind  
 of device, parallelism potential of the face and palmprint  
 recognition algorithms is only lightly exploited on a DSP.  
 That is why, we have also simulated the hardware imple-  
 mentation of the last steps of the processing chain (fea-  
 ture extraction, matching, fusion, and decision) on an FPGA  
 platform.

### 3.2 FPGA Implementation

We work on a Virtex-5-XC5VFX70T FPGA of the Xilinx  
 society.<sup>27</sup> It has been chosen for its configuration: It con-  
 tains, in particular, 128 DSP slices (with  $25 \times 18$  multipli-  
 ers and 48-bit adder/subtractor/accumulator), which support  
 massively parallel digital signal processing algorithms, and  
 22,400 configurable logic blocks (CLBs). Slices of the CLBs  
 can be used to provide logic, arithmetic, and ROM functions;  
 a part of them can also be used as distributing RAM or 32-bit  
 data registers.

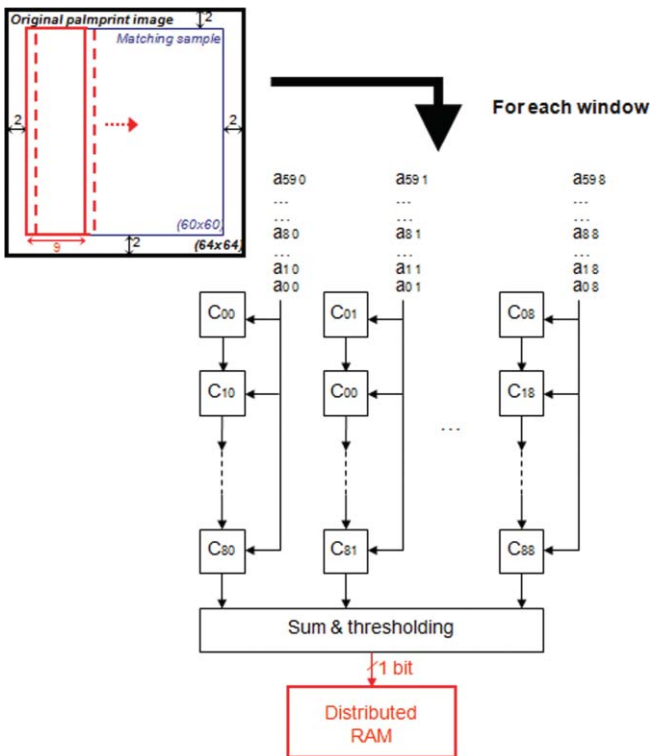
FPGA implementations have been simulated with the Very  
 High-Speed Integrated Circuit, Hardware Description Lan-  
 guage (VHDL) description using the Xilinx ISE tool. Results  
 of the FPGA implementations will be presented in terms of  
 used resources and processing speed. As for the DSP imple-  
 mentation, we have worked on a database of 25 people with  
 two samples per individual in the matching base and we use  
 the sum rule.



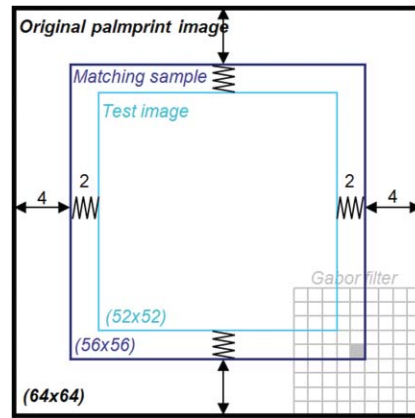
**Fig. 6** Recognition chain hardware realization on FPGA: the software microcontroller core PicoBlaze (PB) controls the feature extraction (FE) and classification (Class) blocks.

404 Figure 6 displays the entire recognition chain. We use  
 405 a PicoBlaze (PB) microcontroller core implemented on the  
 406 FPGA in order to synchronize the two stages of the palm-  
 407 print recognition chain [i.e., the feature extraction (FE) and  
 408 the classification (Class)]. PB is intellectual property of the  
 409 ISE software;<sup>27</sup> this softcore microcontroller is programmed  
 410 in assembly. It triggers the FE block when a palmprint image  
 411 arrives in the FPGA, triggers it again when a face image ar-  
 412 rives, and starts the Class block when the FE block processing  
 413 is finished. When the Class block provides the template num-  
 414 ber, which corresponds to the person's identity, the complete  
 415 system is ready for the next recognition.

416 Figure 7 displays the proposed design of the feature ex-  
 417 traction block. We can see that data parallelism is fully



**Fig. 7** Parallel structure for feature extraction stage: (a) the palmprint image is distributed in successive windows of  $60 \times 9$  pixels, (b) feature extraction is realized using an architecture composed of 9 lines  $\times$  9 columns of DSP slices that perform operations simultaneously.



**Fig. 8** Image sizes during processing: original images =  $64 \times 64$  pixels, training sample images =  $56 \times 56$  pixels because of the convolution with a  $9 \times 9$  Gabor filter, and test images =  $52 \times 52$  pixels because of the  $2 \times 2$  pixels margin introduced by the elastic matching.

418 exploited using the pipeline technique. In agreement with  
 419 Fig. 8, each final test image size is  $52 \times 52$  pixels. Because  
 420 original images are larger than needed, border pixels are  
 421 not used and we work on the  $60 \times 60$  central pixels. In this  
 422 module, the original image is stored in a Block RAM and  
 423 processed by windows of  $60 \times 9$  pixels. The process ends  
 424 after 52 shifts of the vertical window. The convolution op-  
 425 eration is realized using a structure of 81 DSP slices. Each  
 426 of these slices multiplies a received pixel value with a filter  
 427 coefficient and accumulates the previous result.

428 A total of  $61 \times 52 = 3172$  clock cycles are necessary in  
 429 order to run this feature extraction block; 89 DSP slices,  
 430 1 Block RAM and 187 slices are used. The corresponding  
 431 operating frequency is equal to 175 MHz.

432 The classification module consists of the calculation of  
 433 100 elastic Hamming distances ( $25$  templates  $\times 2$  samples  
 434  $\times 2$  biometrics), followed by 50 score fusions (each palm  
 435 score is fused with the corresponding face score), and a  
 436 comparison between each of these fused scores (NN clas-  
 437 sification). The 100 templates have been performed off-  
 438 line and loaded in distributed RAM during the hardware-  
 439 configuration phase. Moreover, each elastic Hamming  
 440 distance is performed by the calculation of 25 Hamming  
 441 distances.

442 Figure 9 illustrates hardware realization of the elastic  
 443 matching stage. We have chosen to carry out this step in 25  
 444 iterations corresponding to the 25 shifts of the elastic dis-  
 445 tance. We have designed a logic block in order to per-  
 446 form horizontal and vertical shift control. At each iteration,  
 447 100 Hamming distances are calculated in parallel.  
 448 An inner loop provides in parallel 100 XOR operation re-  
 449 sults to 100 accumulators. When this loop is completed af-  
 450 ter  $2704 (= 52 \times 52)$  cycles, each accumulator provides a  
 451 Hamming distance value, which can be compared to prece-  
 452 dent values. The 100 minima are stored in registers of the  
 453 FPGA. At the end of the 25 iterations, the fusion occurs  
 454 by summing scores two by two. A final comparison step  
 455 then finds the minimal value among the 50 fused mini-  
 456 ma. The person's identity is given by the corresponding  
 457 template number. A total of  $(2704 + 1) \times 25(\text{XOR}) + 1(\text{sum})$   
 458  $+ 55(\text{final comparison}) = 67681$  clock cycles are necessary  
 459 in order to perform this elastic matching stage.

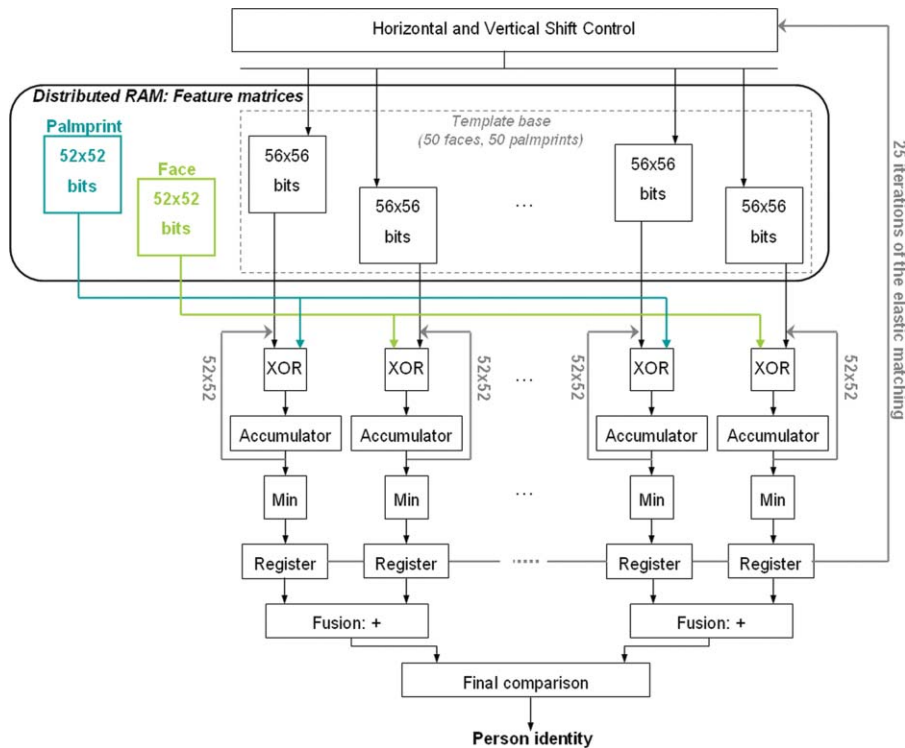


Fig. 9 Implementation of the classification block: for each of the 25 iterations, 100 Hamming distances are performed in parallel.

460 The elastic matching step does not use DSP slice or Block  
 461 RAM but only CLB resources: a total of 8035 slices are used.  
 462 The obtained operating frequency is equal to 175 MHz.

463 The general operating frequency is equal to 175 MHz, it  
 464 corresponds to the frequency of both EM and Class modules.  
 465 Thus, because our processing needs about  $3172 \times 2 + 67681$   
 466 clock cycles, the entire operating time is on the order of  
 467  $423 \mu s$ .

468 Chosen algorithms respect the constraints of simplicity,  
 469 low-cost, regularity, and low-memory use. Thanks to the  
 470 parallelization work, the entire processing is performed in  
 471 only 0.4 ms. Moreover, implementations have been achieved  
 472 using only a portion of the available resources of the Virtex-  
 473 5-XC5VFX70T FPGA (see Table 1). In particular, we use  
 474 very few logical resources (total ratio of 19.1%): because the  
 475 Class block does not use DSP slice but only register slices  
 476 and LUT slices, the number of recognizable people could be  
 477 increased and reach 100.

Table 1 Hardware implementation results of the recognition chain on a Virtex-XC5VFX70T FPGA.

Logic element	Used number	Total number	Used ratio (%)
DSP48 slices	89	128	69.5
Block RAMs	2	148	1.4
Slices	8566	44800	19.1

#### 4 Extensive Experimental Results

##### 4.1 Presentation of Experiments

480 For this feasibility study, we built a database called the uB  
 481 (University of Burgundy) database. It consists of images from  
 482 130 people, with nine face images and nine hand images  
 483 per person. Pairs of images were recorded in three sessions  
 484 of three images. The period of time between each session  
 485 is spread from one day to a few weeks in order to take  
 486 into account luminosity variation and possible variation in  
 487 positioning or appearance. The acquisition environment is  
 488 totally contactless and very user friendly (see Sec. 2.1).

489 In order to verify our approach, we also tested the process-  
 490 ing on a multimodal database, which consists in the fusion of  
 491 two public databases: the Hong Kong Polytechnic University  
 492 (PolyU) palmprint database<sup>28</sup> and the AR face database.<sup>29</sup>  
 493 The PolyU palmprint database contains 7752 gray-scale im-  
 494 ages from 386 different palms. Twenty samples from each of  
 495 these palms were collected in two sessions (of 10 samples).  
 496 The average interval between the first and second collec-  
 497 tion was two months. The size of every original image is  
 498  $384 \times 284$  pixels. Fig. 10 shows some original palm images  
 499 of the PolyU database. They have been obtained with contact  
 500 and pegs in controlled lighting conditions.<sup>30</sup>

501 Our palm extraction method has been adapted to the process-  
 502 ing proposed in Ref. 30: the fixed focal has been taken

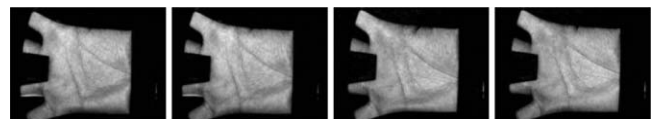
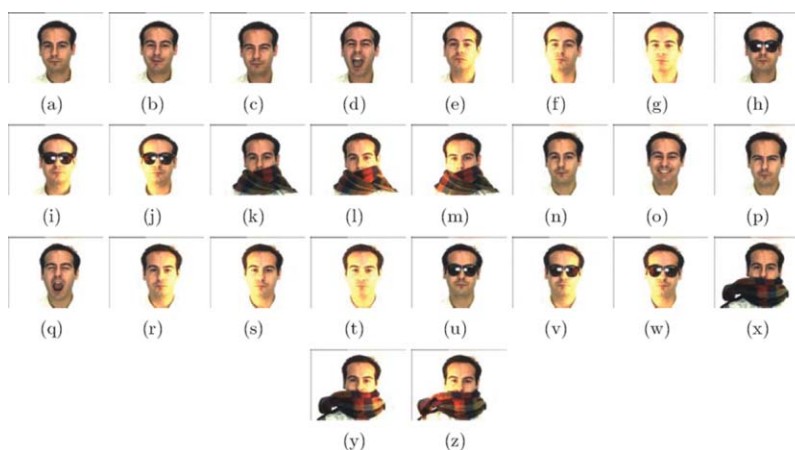


Fig. 10 Four images of the same palm from the PolyU database.





**Fig. 11** Demonstration images of one subject from the AR database: (a–m) are from Session 1 and (n–z) are from session 2.

503 into account by using a fixed size window when defining  
 504 the ROI. Algorithms have also been adapted to the number  
 505 of visible fingers, which is no longer 5. Palmprints are still  
 506 rotated and scaled to the size of  $64 \times 64$  pixels.

507 The AR face database is composed of  $\sim 4000$  color face  
 508 images of 126 people (70 men and 56 women), including  
 509 frontal views of faces with different facial expressions, under  
 510 different lighting conditions, and with various occlusions<sup>29</sup>  
 511 (see Fig. 11). Face images were acquired in two sessions  
 512 separated by two weeks. Each session captured 13 color  
 513 images. The two sessions are available for 119 individuals.  
 514 The preprocessing is the same as that of the uB database:  
 515 all color images are transformed into gray-level images and  
 516 each image (of  $768 \times 576$  pixels) is scaled down to  $64 \times 64$   
 517 pixels.

518 We take sample subsets of the same size from these two  
 519 databases in order to create the multimodal database. As Jing  
 520 et al.,<sup>6</sup> we use the first 119 palmprint classes with each class  
 521 containing all 20 samples and all 119 face classes with each  
 522 class including the first 20 samples.

523 The two Gabor filters have been chosen empirically on the  
 524 uB database and applied to both uB and AR-PolyU databases.  
 525 The way the Gabor filter coefficients have been chosen is  
 526 explained in Ref. 14. Actually, the chosen filter is the same  
 527 for the two modalities: its coefficients are set as  $\lambda = 8.20$  and  
 528  $\Theta = 2\pi/8$ .

529 In this paper, all the results take into account the con-  
 530 straints of the hardware implementation. The preprocessing  
 531 algorithms have been adapted to fixed-point calculation (for  
 532 their DSP implementation), and the remaining processing  
 533 has been quantified (for their FPGA implementation). In this  
 534 way, results of the hardware system can be compared to those  
 535 of the algorithmic system presented in Ref. 14.

## 536 4.2 Recognition Performance

537 The uB database contains  $130 \times 9 = 1170$  images of each  
 538 modality. For the recognition tests, it is divided in two parts:  
 539 the training sample set and test sample set. As we respect  
 540 the small sample set constraint, the number of samples per  
 541 person in the matching base varies from 1 to 3. We defined  
 542 two different protocols to conduct our experiments. Proto-  
 543 col 1: samples of the matching base are picked up randomly  
 544 among the nine available ones, and all the remaining samples  
 545 are used for tests. Protocol 2: samples of the matching base

546 are picked up randomly among the three available ones of a  
 547 unique session, and only the samples of the two other sessions  
 548 are used for tests. Thus, when the matching base contains  
 549  $n$  samples per person ( $n \in \{1, 2, 3\}$ ),  $(9 - n) \times 130$  tests are  
 550 performed according to the protocol 1 and  $6 \times 130 (= 780)$   
 551 according to the protocol 2. Protocol 1 is the most used in  
 552 studies because it allows one to take into consideration all the  
 553 information contained in the database. Protocol 2 is used to  
 554 verify the robustness of the algorithm in more realistic condi-  
 555 tions: in the real world, all the matching samples are acquired  
 556 during the enrollment phase, so the captured variability is  
 557 reduced.

558 Results are qualified by the *recognition rate*, which is the  
 559 ratio between the number of correct classification results and  
 560 the total number of tests. Because it depends on the selected  
 561 samples, nine tests with nine different matching bases are  
 562 performed (for a matching base built according to protocol 2  
 563 in the three samples cases, only three tests are performed,  
 564 since it is only possible to build three different bases). They  
 565 are then averaged to constitute a final result [the for aver-  
 566 aged recognition rate (ARR)], which objectively describes  
 567 the performance of the system.

568 Results obtained thanks to the protocol 1 are given in  
 569 Table 2. They are very similar to those of our former  
 570 algorithmic study:<sup>14</sup> quantification of the Gabor filtering and  
 571 transition to fixed-point do not introduce any performance  
 572 degradation. As with the algorithmic model, the palmprint

**Table 2** Average recognition rate obtained according to the protocol 1 on the uB database.

Method	ARR (%) one sample	ARR (%) two samples	ARR (%) three samples
Face recognition	$79.10 \pm 2.71$	$90.93 \pm 4.60$	$95.25 \pm 6.93$
Palm recognition	$91.05 \pm 1.22$	$96.82 \pm 1.52$	$98.27 \pm 1.84$
Minimum score	$92.43 \pm 1.70$	$97.40 \pm 2.12$	$98.79 \pm 2.63$
Summed score	$96.02 \pm 0.95$	$98.96 \pm 0.71$	$99.59 \pm 0.76$
Multiplied score	$96.38 \pm 0.94$	$99.07 \pm 0.65$	$99.61 \pm 0.79$

**Table 3** Average recognition rate obtained according to the protocol 2 on uB the database.

Method	ARR (%) one sample	ARR (%) two samples	ARR (%) three samples
Face recognition	73.50 ± 2.35	81.85 ± 2.19	84.96 ± 2.52
Palm recognition	89.32 ± 1.54	94.06 ± 1.26	95.56 ± 0.85
Minimum score	90.16 ± 1.51	93.69 ± 1.04	94.74 ± 1.22
Summed score	94.89 ± 0.82	97.68 ± 0.66	98.46 ± 0.56
Multiplied score	95.31 ± 0.77	97.89 ± 0.62	98.42 ± 0.52

**Table 4** Average recognition rate obtained with 20 random tests for each method using the AR-PolyU database.

Method	ARR (%) one sample	ARR (%) two samples	ARR (%) three samples
Face recognition	68.22 ± 3.36	83.69 ± 10.4	86.21 ± 9.97
Palm recognition	85.46 ± 1.29	93.90 ± 0.77	96.03 ± 0.58
Minimum score	71.95 ± 2.78	86.15 ± 9.66	88.27 ± 9.13
Summed score	92.04 ± 1.18	97.49 ± 0.95	98.48 ± 0.63
Multiplied score	92.99 ± 1.11	97.92 ± 1.70	98.66 ± 1.25

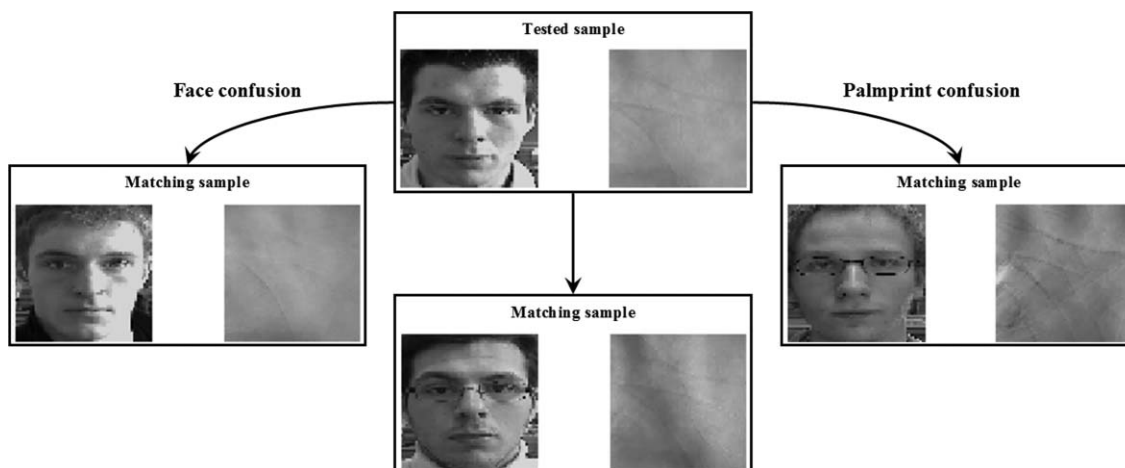
573 recognition chain achieves, alone, a high-performance level.  
 574 Face recognition does not perform as well as palm recogni-  
 575 tion, but results are rather high for such a low-computational-  
 576 cost method in natural illumination conditions. Fusion  
 577 always performs better than unimodality, and the difference  
 578 between fusion methods is low: averaged recognition rates  
 579 differ only by a few tenths. Considering the computational  
 580 cost and the results of each method, the addition is very  
 581 interesting in our case. Minimum has a low complexity  
 582 but does not give good results, and the small performance  
 583 increase induced by the multiplication does not compensate  
 584 the difference of cost. There is a high similarity between the  
 585 sum and multiplication rules. Very good results are obtained  
 586 in the two-samples case: error is  $\sim 1\%$ . It can be noted  
 587 that performance grows substantially between the one- and  
 588 two-sample cases, while the increase between the two-  
 589 and three-samples cases is minor.

590 Results obtained thanks to protocol 2 are presented in  
 591 Table 3. As expected, they are generally not as good as those  
 592 obtained according to protocol 1. However, they are still high:  
 593 ARR after fusion is between 94.9% in the one-sample case  
 594 and 98.5% in the two-sample case. All the comments made  
 595 for the Table 2 are applicable to Table 3: fusion allows one to  
 596 substantially increase the performance, there is only a small  
 597 difference between addition and multiplication, and the gap  
 598 between the one- and two-sample cases is significant. The

599 only difference lies in the results of the minimum fusion,  
 600 which does not bring a performance increase to the palm-  
 601 print recognition. Moreover, we can see that fusion is more  
 602 robust than monomodality: when the variability captured in  
 603 the sample base decreases, the standard deviation of the face  
 604 and palm results are greatly reduced, whereas it keeps similar  
 605 values for the fusion.

606 Table 4 illustrates the average results of 20 random tests  
 607 conducted on AR-PolyU database according to the protocol  
 608 described in Ref. 6. We can see that all trends revealed by the  
 609 tests conducted on the uB database are confirmed on these  
 610 public databases.

611 For the face, errors are typically caused by the occasional  
 612 wear of accessories (such as glasses) and by changes in ex-  
 613 pression or pose. For the palm, they are often due to a lack  
 614 of image quality (bad focus, inhomogeneous illumination,  
 615 etc.). These criteria are not correlated. That is why, most  
 616 of the time, only one modality fails when a pair of images  
 617 is tested. The fusion of the two often brings enough infor-  
 618 mation to override the confusion: for example, the sum of  
 619 two small distances (calculated on the samples of the same  
 620 user) can be smaller than the sum between a very small dis-  
 621 tance (calculated on the samples, which are confused) and a  
 622 large one (calculated on the samples of the other modality,  
 623 which are not confused). Sometimes, both modalities are mis-  
 624 taken, but the overall system succeeds, as in Fig. 12. This is

**Fig. 12** Example of overall system success despite failure of the monomodal systems.

**Table 5** Small sample biometric recognition performance comparison using the AR face database and PolyU palmprint database. Average recognition rate in the two- and three-sample cases.

Method	ARR (%) two-samples case			ARR (%) three-samples case		
	Face	Palm	Fusion	Face	Palm	Fusion
Jing et al.	65.67	63.33	92.66	74.88	64.29	96.14
Proposed method	83.69	93.90	97.49	86.21	96.03	98.48

<sup>a</sup>Reference 6.

probably because the two modalities are confused with samples of two different users, which cannot occur when they are fused because they are considered simultaneously.

### 4.3 Verification Performance

Performance of biometric verification systems is measured in terms of false rejection rate (FRR), which consists in the error rate in the intraclass comparisons, and false acceptance rate (FAR), which is computed from the interclass comparisons. A given FRR is achieved at a fixed FAR, and vice versa. By varying the FRR (or the FAR), the receiver operating characteristic (ROC) curve is obtained. In order to judge the performance of a verification algorithm, it is usual to use the operating point where the FAR and FRR are equal. It corresponds to the so-called equal error rate (EER).

In biometric verification systems, the test person is compared to a single reference person and a decision is made whether the two are identical or not. That is why biometric verification usually needs more images per individual for training in order to capture intraclass variability. Therefore, biometric verification often suffers more from the small sample size problem than biometric recognition.<sup>19</sup>

As for the biometric recognition, we arbitrarily take 1–3 samples of each of the 130 individuals in order to build the training set. The remainder is used as test set. We com-

pared each test sample to all training samples: for a given test sample of the uB database, we perform genuine tests with the samples of its own class, and impostor tests with the samples of the other 129 classes. For example, in the three-samples case, the system tests 780 (130×6) genuine users and 100,620 (130×129×6) impostors.

Table 6 gathers EERs calculated in the one-, two-, and three-sample cases on the uB and AR-PolyU databases, and Fig. 13 displays the ROC curves in the one-sample case. It has to be noted that all results correspond to average verification rates obtained by averaging the verifications rates of 9 or 20 random tests. We can see that verification follows the same trends as recognition: palm achieves good performance alone and fusion allows one to greatly improve the results. Figure 13 shows that the curve behavior is the same on the two multimodal databases and that fusion by addition and multiplication is very similar.

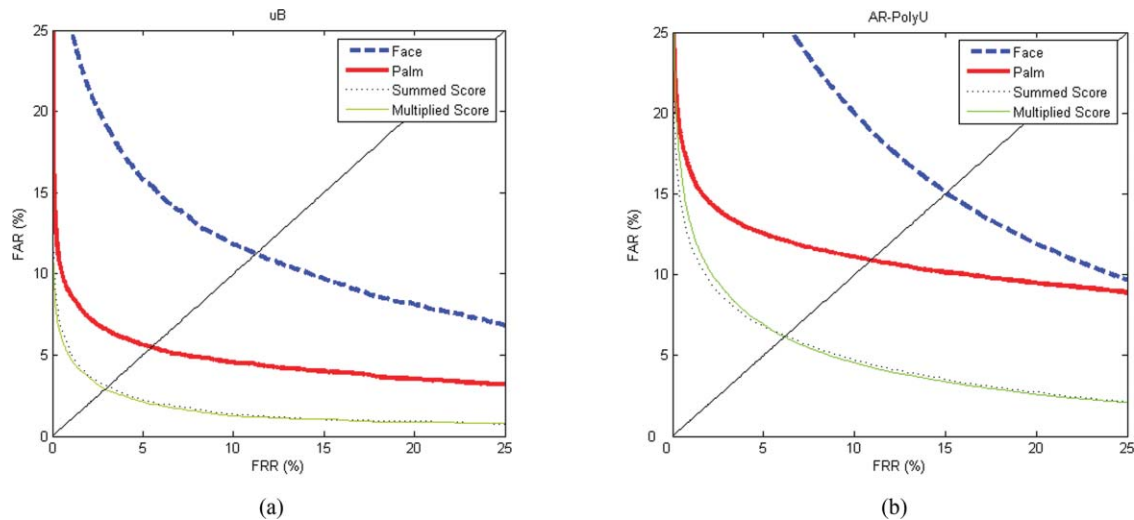
## 5 Discussion

Proposed system not only reach good performance in terms of hardware implementation, but also in terms of experimental results: it obtains similar results to those we can find in the literature. In the same conditions of biometric recognition on the AR-PolyU database, Jing et al.<sup>6</sup> obtain slightly lower performance, which keeps the same trends (see Table 5). For this, they use a Gabor feature

**Table 6** Average equal error rate comparison for biometric verification. The bottom two rows correspond to the results obtained by Kumar et al.<sup>9</sup> without using (A) and using (B) subject-claimed identity.

Method	Database	Sample Size	AEER (%)		
			Face	Palm	Fusion
Proposed method	AR-PolyU	1	15.1	10.9	6.21
Proposed method	AR-PolyU	2	7.07	4.62	2.38
Proposed method	uB	1	11.2	5.43	3.12
Proposed method	uB	2	5.22	2.23	1.10
Proposed method	uB	3	3.54	1.53	0.79
Kumar et al. (A) <sup>a</sup>		4	5.48	5.24	2.21
Kumar et al. (B) <sup>a</sup>		4	4.28	4.45	0.72

<sup>a</sup>Reference 9.



**Fig. 13** ROC curves of biometric verification in the one-sample case calculated on (a) the uB database and (b) the AR-PolyU multimodal database.

675 fusion followed by a feature compression using a  
 676 Kernel Discriminative Common Vectors (KDCVs) approach  
 677 and a classification by the radial basis function (RBF)  
 678 network.

679 Kumar et al.<sup>9</sup> propose a score fusion using a feed-forward  
 680 neural network trained on a base of four samples per person.  
 681 Face features are extracted by the Eigenface method, and  
 682 palmprint by the combination of four directional filters. The  
 683 proposed method is tested on a multimodal database designed  
 684 by the authors that contains 70 subjects and is acquired in  
 685 more controlled conditions (for example, illumination, dis-  
 686 tance between hand and sensor). Table 6 tries to make some  
 687 biometric verification performance comparisons between the  
 688 two bimodal systems. Kumar et al.<sup>9</sup> show that combining sub-  
 689 ject claimed identity allows one to reduce verification error  
 690 (EER from 2.21 to 0.72%). On the uB database with only  
 691 three samples, we also obtain better performance than this  
 692 reference method, which does not use the claimed identity,  
 693 and our EER is very similar to the one obtained using claimed  
 694 subject identity. Results obtained with AR-PolyU in the two-  
 695 sample case are also comparable to those of the reference  
 696 method.

697 It must be noted that performance calculated on the AR-  
 698 PolyU database is not as good as that calculated on the uB  
 699 database because hand images are of lower quality and do not  
 700 show the entire hand, which makes palm extraction less accu-  
 701 rate. Moreover, faces are not acquired in the same conditions  
 702 and show a large white background.

703 In terms of hardware implementation, as Yang and  
 704 Paindavoine<sup>11</sup> or Lopez-Ongil et al.<sup>12</sup> (who work on face  
 705 and hand geometry recognition, respectively), we prove that  
 706 FPGA implementation is highly better than DSP (or general  
 707 purpose processor) implementation. For Ref. 11 and 12 execu-  
 708 tion time is multiplied by 3, and in our case it is multiplied  
 709 by 17. This high coefficient is achieved because we work on  
 710 very short time (0.4 ms for FPGA and 7 ms for DSP) and  
 711 use massive parallelism on FPGA. If we compare the work  
 712 of Yoo et al.<sup>13</sup> on multimodal recognition to ours, then we  
 713 can see that with comparable EER (1.5% for the iris, for  
 714 example), execution times are better (total execution time of  
 715 <500 ms for us and ~1 s for the iris in Ref. 13).

We observe that with a sequential architecture the execu-  
 tion time of the last steps of processing depends on the  
 number of subjects in the comparison base. However, thanks  
 to the parallel architecture of the FPGA implementation,  
 recognition of 50 or more individuals could be realized using  
 the same chip (FPGA Virtex-XC5VFX70T) with the same  
 processing speed. On the other hand, authentication would  
 be even faster on DSP because the comparison base would  
 contain the samples of a single user.

## 6 Conclusion and Perspectives

In this paper, we have presented a contactless biometric sys-  
 tem that combines two modalities: palmprint and face. A  
 complete processing chain has been developed from the ac-  
 quisition of hand and face images to classification decision,  
 and a hardware architecture has been implemented on DSP  
 and FPGA. Face and palmprint are two decorrelated modal-  
 ities, that can be acquired easily with minimal equipment  
 (a webcam) and without contact. Multimodal systems have  
 many advantages over monomodal systems, such as better  
 robustness or greater universality. Therefore, using these two  
 biometrics in a multimodal system ensures one to create an  
 efficient general public system.

As we work on palmprint in a contactless context, a hand  
 preprocessing (which consists of a palm extraction) has been  
 developed and simulated on a DSP platform. Hardware im-  
 plementation of the rest of the multimodal recognition chain  
 has been simulated on the DSP and on a FPGA Virtex-5 de-  
 vice. Hardware results demonstrate that preprocessing can  
 easily be performed during the acquisition phase, and multi-  
 modal biometric recognition can be treated almost instantly.  
 Only 0.4 ms are necessary using 50 training samples recorded  
 on 25 persons with low-resource consumption on FPGA,  
 while no more than 7 ms are needed on DSP.

A database of 2340 images (130 subjects  $\times$  2 modalities  
 $\times$  9 views) was built in real-world conditions (user-friendly  
 interface and natural illumination, for example). Experimen-  
 tal results show that multimodal fusion always reaches better  
 performance than monomodality. The proposed algorithm,  
 which is based on low-complexity operations, such as Gabor  
 filtering and similarity measurement by binary comparison,

fits palmprint recognition particularly well. The fusion of palmprint and face at score level allows us to achieve high recognition rates (98.96% using uB database and 97.49% using AR-PolyU database with only two training samples per person and per modality). In the same manner, the used fusion strategy provides good performance for the biometric verification task (EER = 1.10% in the two sample case). We can note that the adaptation of the algorithms to hardware implementation do not introduce performance degradation. Our experiments demonstrate that the proposed approach is an effective solution for the small sample biometric problem and can outperform memory-consuming methods, such as the ones that use Gabor filter banks. Moreover, using the same algorithm, performance may be increased with other modalities having an oriented texture such as knuckleprint or ear.

This soft- and hardware study shows the feasibility of a robust and efficient embedded multimodal biometric system that offers several advantages; for example, flexibility, user-friendliness, and real-time processing. Besides, the proposed system is able to work with real-world application challenges, such as lighting changes and variations in hand position and orientation. Our final objective is to implement the complete biometric application on a hardware system. Our next step consists of doing new processing optimizations and complexity analysis of the palmprint image extraction task (hand localization, palmprint extraction and normalization), before achieving FPGA implantations. The chosen FPGA contains a PowerPC processor core that could be used to perform some calculations.

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Q3

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