Research Article

Color-Based Image Retrieval Using Perceptually Modified Hausdorff Distance

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In most content-based image retrieval systems, the color information is extensively used for its simplicity and generality. Due to its compactness in characterizing the global information, a uniform quantization of colors, or a histogram, has been the most commonly used color descriptor. However, a cluster-based representation, or a signature, has been proven to be more compact and theoretically sound than a histogram for increasing the discriminatory power and reducing the gap between human perception and computer-aided retrieval system. Despite of these advantages, only few papers have broached dissimilarity measure based on the cluster-based nonuniform quantization of colors. In this paper, we extract the perceptual representation of an original color image, a statistical signature by modifying general color signature, which consists of a set of points with statistical volume. Also we present a novel dissimilarity measure for a statistical signature called Perceptually Modified Hausdorff Distance (PMHD) that is based on the Hausdorff distance. In the result, the proposed retrieval system views an image as a statistical signature, and uses the PMHD as the metric between statistical signatures. The precision versus recall results show that the proposed dissimilarity measure generally outperforms all other dissimilarity measures on an unmodified commercial image database.

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1. INTRODUCTION

With an explosive growth of digital image collections, content-based image retrieval (CBIR) has been emerged as one of the most active and challenging problems in computer vision as well as multimedia applications. Content-based image retrieval differs from the traditional text-based image retrieval in that images would be indexed by the visual features, such as color, texture, and shape [1–3]. In order to reflect the human perception precisely, there have been lots of image retrieval systems, which are based on the query-by-example scheme, including QBIC [4], PhotoBook [5], VisualSEEK [6], and MARS [7]. Actually, low-level visual contents do not properly capture human perceptual concepts, so closing the gap between them is still one of the ongoing problems. However, a series of psychophysical experiments reported that there is a significant correlation between visual features and semantically relevant information [8]. Based on these findings, many techniques have been introduced to improve the perceptual visual features and dissimilarity measures, which enable to achieve semantically correct retrieval performances [1, 9–14].

Among variety of visual features, color information is the most frequently used visual characteristic. Color histogram (or fixed-binning histogram) is widely employed as a color descriptor due to its simplicity of implementation and insensitivity to similarity transformation [9, 15]. However, in some cases, these simple histogram-based indexing methods fail to match perceptual (dis)similarity [16]. Moreover, since the color histogram is sensitive to the variation in color distribution, the performances of these methods usually depend severely on the quantization process in color space. To overcome these drawbacks, a clustering-based representation, signature (or adaptive-binning color histogram) has been proposed [12–14, 16–21]. Based on the psychophysical fact that at the first perception stage the human visual system identifies the dominant colors and cannot simultaneously perceive a large number of colors [12], cluster-based techniques generally extract dominant colors and their proportions to describe the overall color information. Also, a signature represents a set of clusters compactly in a color space and the distribution of color features. Therefore, it can reduce the complexity of representation and the cost of retrieval process.
Once two sets of visual features, represented by a histogram or a signature, are given, we need to determine how similar one is from the other. A number of different dissimilarity measures have been proposed in various areas of computer vision. Specifically for histograms, Jeffrey divergence, histogram intersection, and $\chi^2$-statistics have been known to work successfully. However, these dissimilarity measures cannot be directly applied to signatures. As alternatives to these metrics, Rubner and Tomasi [16] proposed a novel dissimilarity measure for matching signatures, the Earth Mover’s distance (EMD), which was able to overcome most of the drawbacks in histogram-based dissimilarity measures and handle the partial matching between two images. Dorado and Iizquierdo [17] also used the EMD as a metric to compare fuzzy color signatures. However, the computational complexity of the EMD is very high compared to other dissimilarity measures. Leow and Li [19] proposed a new dissimilarity measure called weighted correlation (WC) for signatures, which is more reliable than Euclidean distance and computationally more efficient than EMD. Generally, WC produced better performance than that of EMD, however in some cases, it showed worse results than those of the Jeffrey divergence (ID) [22]. Mojsilović et al. [12] introduced perceptual color distance metric, optimal color composition distance (OCCD), which is based on the optimal mapping between the dominant color components with area percentage of two images.

In this paper, we extract the compact representation of an original color image, a statistical signature by modifying general color signature, which consists of the representative color features and their statistical volume. Then a novel dissimilarity measure for matching statistical signatures is proposed based on the Hausdorff distance. The Hausdorff distance is an effective metric for the dissimilarity measure between two sets of points [23–25], that is also robust to the outliers and geometric variations in certain degree. Recently, it has been applied to video indexing and retrieval [26]. However, it was simply designed for color histogram model. To overcome this drawback, we propose a new perceptually modified Hausdorff distance (PMHD) as a measure of dissimilarity between statistical signatures, that is consistent with human perception. Moreover, to cope with the partial matching problem, a partial PMHD metric is designed by incorporating outlier detection scheme. The experimental results on a real image database show that the proposed metric outperforms other conventional dissimilarity measures.

This paper is organized as follows. In Section 2, we introduce a statistical signature as a color descriptor. Section 3 proposes a novel dissimilarity measure, PMHD, and partial PMHD for partial matching. Then, Section 4 presents the experimental results and discussions on the effectiveness of the proposed metric. Finally, conclusions are drawn in Section 5.

2. A COLOR IMAGE DESCRIPTOR: A STATISTICAL SIGNATURE

In order to retrieve visually similar images to a query image using color information, a proper color descriptor for the images should be designed. Recently, it has been proven that a signature can describe the color distribution more efficiently than a color histogram [16, 17, 19]. And a signature is appropriate for describing each image independently of other images in an image database.

In this paper, we represent an original color image by a statistical signature defined as

$$\delta = \{ (s_i, w_i, \Sigma_i) | i = 1, \ldots, N \},$$

where $N$ is the number of clusters, $s_i$ is the mean feature vector of $i$th cluster, $w_i$ is the number of the features that belong to $i$th cluster, and $\Sigma_i$ is the covariance matrix of $i$th cluster. Variety of different clustering methods can be used to construct a statistical signature from a color image. In this paper, we used $k$-means algorithm [27] to cluster color features in CIELab color space.

Figure 1 shows two sample images quantized by using the proposed statistical signature. We could observe that not much perceptual color degradation has occurred, regardless of a great amount of representation data reduction in color space by the clustering.

3. A NOVEL DISSIMILARITY MEASURE FOR A STATISTICAL SIGNATURE

3.1. Hausdorff distance

It has been shown that the Hausdorff distance (HD) is an effective metric for the dissimilarity measure between two sets of points in a number of computer vision literatures [23–25, 28], while insensitive to the variations and noise.

In this section, we briefly describe the HD. More details can be found in [23–25, 28]. Given two finite point sets, $P_1 = \{ p_1, \ldots, p_{N_1} \}$ and $P_2 = \{ p_1^{'}, \ldots, p_{N_2}^{'} \}$, the HD is defined as

$$D_H = (P_1, P_2) = \text{Max} \{ d_H(P_1, P_2), d_H(P_2, P_1) \},$$

where

$$d_H(P_1, P_2) = \max_{p_1 \in P_1} \min_{p_2 \in P_2} \| p_1 - p_2 \|,$$

and the function $d_H$ is the directed HD between two point sets.

3.2. Perceptually modified Hausdorff distance

In this paper, we propose a novel dissimilarity, called perceptually modified Hausdorff distance (PMHD) measure based on HD for comparison of statistical signatures.

Given two statistical signatures, $\delta_1 = \{ (s_i^1, w_i^1, \Sigma_i^1) | i = 1, \ldots, N \}$ and $\delta_2 = \{ (s_j^2, w_j^2, \Sigma_j^2) | j = 1, \ldots, M \}$, a novel dissimilarity measure between two statistical signatures is defined by

$$D_H(\delta_1, \delta_2) = \text{Max} \{ d_H(\delta_1, \delta_2), d_H(\delta_2, \delta_1) \},$$

where $d_H(\delta_1, \delta_2)$ and $d_H(\delta_2, \delta_1)$ are directed Hausdorff distances between two statistical signatures.
The directed Hausdorff distance is defined as
\[
d_H(\delta_1, \delta_2) = \frac{\sum_i \left[ w_i \times \min_j \left( \frac{d(s_i^1, s_j^1)}{\min(w_i, w_j)} \right) \right]}{\sum_i w_i^1},
\]
where \(d(s_i^1, s_j^1)^1\) is the distance between two color features, \(s_i^1\) and \(s_j^1\) in \(\delta_1\) and \(\delta_2\), respectively. In this paper, we consider three different distances for \(d(s_i^1, s_j^1)^1\): the Euclidean distance, the CIE94 color difference, and the Mahalanobis distance. In order to guarantee that the distance is perceptually uniform, the CIE94 color difference equation is used instead of the Euclidean distance in CIELab color space [29, 30]. While the Euclidean distance and the CIE94 simply measure the geometric distance between two feature vectors in the Euclidean coordinates without considering the distribution of color features, the Mahalanobis distance explicitly considers the distribution of color features after clustering process [31]. Three distances are defined as follows.

(i) Euclidean distance:
\[
d_E(s_i^1, s_j^1) = \sqrt{\sum_{k=1}^3 \left( s_i^1(k) - s_j^1(k) \right)^2},
\]
where \(s_i^1(k)\) and \(s_j^1(k)\) are the kth elements of \(s_i^1\) and \(s_j^1\), respectively.

(ii) CIE94 color difference:
\[
d_{\text{CIE94}}(s_i^1, s_j^1) = \left[ \left( \frac{\Delta L^*}{k_L S_L} \right)^2 + \left( \frac{\Delta C^*}{k_C S_C} \right)^2 + \left( \frac{\Delta H^*}{k_H S_H} \right)^2 \right]^{1/2},
\]
where \(\Delta L^*\), \(\Delta C^*\), and \(\Delta H^*\) are the differences in lightness, chroma, and hue between \(s_i^1\) and \(s_j^1\),

(iii) Mahalanobis distance:
\[
d_M(s_i^1, s_j^1) = (s_j^2 - s_i^2) \mathbf{S}^{-1} (s_j^2 - s_i^2),
\]
where \(\mathbf{S}\) is the covariance matrix of the color features.

Note that in order to take into account the size of clusters in matching, we penalize the distance between two color feature vectors by the minimum of their corresponding sizes as in (5). This reflects the fact that color features with a large size influence more the perceptual similarity between images than the smaller ones [12]. Let us consider an example as in Figure 2(a). There are two pairs of feature vectors denoted by circles centered at the mean feature vectors. The radius of each circle represents the size of the corresponding feature. If we compute only the geometric distance without considering the size of two feature vectors, two distances \(d_1\) and \(d_2\) will be equal. However, perceptually \(d_1\) must be smaller than \(d_2\). Another example is given in Figure 2(b), where three feature vectors are shown. Again, if we consider only the geometric distance, \(d_1\) will be smaller than \(d_2\). However, in fact, perceptual \(d_2\) is smaller than \(d_1\).

Thus, by combining the set theoretical metric and perceptual notion in the dissimilarity measure, the proposed PMHD becomes relatively insensitive to the variations of mean color features in a signature, and consistent with human perception.

### 3.3. Partial PMHD metric for partial matching

In certain cases, a user may have a partial information of the target images as the query, or wants to extract all the images including partial information of the query. In these cases, conventional techniques with global descriptor are not appropriate. Like a color histogram, a signature is also a global descriptor of a whole image. So, the direct application of the HD as in (4) cannot cope with occlusion and clutter in image retrieval or object recognition [16, 28, 32]. In order to handle partial matching, Huttenlocher et al. [23] proposed a partial HD based on ranking, which measures the difference between portions of point sets. Also, Azencott et al. [25] further modified the rank-based partial HD by order statistics. But, these distances were shown to be sensitive to the parameter changes. In order to address these problems, Sim et al. [28] proposed two robust HD measures, M-HD and LTS-HD, based on the robust statistics such as M-estimation and least trimmed square (LTS). Unfortunately, they are not appropriate for image retrieval system because they are computationally too complex to search a large database.
In this paper, in order to remedy the partial matching problem, we detect and exclude the outliers first by an outlier test function, and then apply the proposed PMHD to the remaining feature points. Let us define the outlier test function by

\[ f(i) = \begin{cases} 
1, & \text{if } \frac{d(s_i^1, s_j^2)}{\min(w_i^1, w_j^2)} < D_{th}, \\
0, & \text{otherwise,}
\end{cases} \]  

(9)

where \( D_{th} \) is a prespecific threshold for the outlier detection. The above function indicates that \( s_i^1 \) is inlier if \( f(i) = 1 \), otherwise outlier.

Now let us define two directed Hausdorff distances with and without outliers by

\[ d_H^t(s_1, s_2) = \frac{\sum_i w_i^1 \times \min_j \{d(s_i^1, s_j^2)/\min(w_i^1, w_j^2)\}}{\sum_i w_i^1}, \]

\[ d_H^w(s_1, s_2) = \frac{\sum_i w_i^1 \times \min_j \{d(s_i^1, s_j^2)/\min(w_i^1, w_j^2)\} \times f(i)}{\sum_i w_i^1 \times f(i)}, \]  

(10)

respectively.

Then the new modified directed partial PMHD is obtained by

\[ d_H^p(s_1, s_2) = \begin{cases} 
\frac{\sum_i w_i^1 \times f(i)}{\sum_i w_i^1} > P_{th}, \\
\frac{\sum_i w_i^1 \times f(i)}{\sum_i w_i^1}, & \text{otherwise,}
\end{cases} \]  

(11)

where \( P_{th} \) is a prespecific threshold for the control of a fraction of information loss.

4. EXPERIMENTAL RESULTS

4.1. The database and queries

To evaluate the retrieval precision and recall performance of the proposed retrieval system, several experiments have been conducted on a real database. We used 5200 images selected from commercially available Corel color image database without any modification. There are 52 semantic categories, each of them containing 100 images. Among those, we have chosen four sets of data including Cheetah, Eagle, Pyramids, and Royal guards as the query. Some example images in the queries are shown in Figure 3. We note in Figure 3 that since the original categorization of images was not based on the color information, substantial amount of variations in color still exist even in the same category. Nonetheless, in this experiment, we used all images in these four categories as queries.

We computed a precision and recall pair to all query categories, which is commonly used as the retrieval performance measurement [33]. The precision \( P \) and recall \( R \) are defined as

\[ P = \frac{r}{n}, \quad R = \frac{r}{m}, \]  

(12)

where \( r \) is the number of retrieved relevant images, \( n \) is the total number of retrieved images, and \( m \) is the total number of relevant images in the whole database.

The precision \( P \) measures the accuracy of the retrieval and the recall \( R \) measures the effectiveness of the retrieval performance.

4.2. Retrieval results for queries

The performance of the proposed PMHD was compared with five well-known dissimilarity measures, including histogram intersection (HI), \( \chi^2 \)-statistics, Jeffrey divergence (JD), and quadratic form (QF) distance, for the fixed binning histogram, and EMD for the signature.

Let \( H_1 \) and \( H_2 \) represent two color histograms or signatures. Then, these five dissimilarity measures are defined as follows.

\[ d(H_1, H_2) = 1 - \frac{\sum_i \min(h_i^1, h_i^2)}{\sum_i h_i^2}, \]  

(13)

where \( h_i^j \) is the number of elements in the \( i \)th bin of \( H_j \).
Figure 3: Example query images from four categories in the Corel database. (a) Eagle, (b) Cheetah, (c) Pyramids, and (d) Royal guards.

(2) \( \chi^2 \)-statistics:

\[
d(H_1, H_2) = \sum_i \frac{(h_1^i - m_i)^2}{m_i},
\]

where \( m_i = (h_1^i + h_2^i)/2 \).

(3) Jeffrey divergence (JD) [22]:

\[
d(H_1, H_2) = \sum_i \left( h_1^i \log \frac{h_1^i}{m_i} + h_2^i \log \frac{h_2^i}{m_i} \right),
\]

where again \( m_i = (h_1^i + h_2^i)/2 \).
(4) Quadratic form (QF) distance [4, 35]:
\[ d(H_1, H_2) = \sqrt{(H_1 - H_2)^T A (H_1 - H_2)}, \]
where \( A \) is a similarity matrix that encodes the cross-bin relationships based on the perceptual similarity of the representative colors of the bins.

(5) EMD [16, 36]:
\[ d(H_1, H_2) = \frac{\sum_{i,j} g_{ij} d_{ij}}{\sum_{i,j} g_{ij}}, \]
where \( d_{ij} \) denotes the dissimilarity between the \( i \)th and \( j \)th bins, and \( g_{ij} \) is the optimal flow between two distributions. The total cost \( \sum_{i,j} g_{ij} d_{ij} \) is minimized subject to the constraints,
\[
\begin{align*}
g_{ij} & \geq 0, & \sum_i g_{ij} & \leq h_i^2, & \sum_j g_{ij} & \leq h_j^2, \\
\sum_{i,j} g_{ij} & = \min \left( \sum_i h_i^2, \sum_j h_j^2 \right).
\end{align*}
\]

As reported in [36], EMD yielded a very good retrieval performance for the small sample size, while JD and \( \chi^2 \) performed very well for the larger sample sizes. Leow and Li [19] proposed the novel dissimilarity measure, weighted correlation (WC) which can be used to compare two histograms with different binnings. In the image retrieval, the performance of WC was comparable to other dissimilarity measures, but not good as JD. Therefore, in this paper, we evaluated only the performance of JD.

In order to represent a color image as a fixed histogram representation, the RGB color space was uniformly partitioned into \( 10 \times 10 \times 10 = 1000 \) color bins. And a color was quantized to the mean centroid of the cubic bin. While, as mentioned in Section 2, a statistical signature was extracted based on a statistical signature containing 10 color feature vectors.

Table 1: The best parameters for partial matching: (\( D_{th}, P_{th} \)).

| Query          | Mahalanobis | Distances | Euclidean | CIE94  |
|----------------|-------------|-----------|-----------|--------|
| Eagle          | (50, 0.6)   | (50, 0.7) | (50, 0.8) |
| Cheetah        | (80, 0.8)   | (90, 0.9) | (90, 0.9) |
| Pyramids       | (100, 0.7)  | (50, 0.6) | (30, 0.6) |
| Royal guards   | (30, 0.6)   | (100, 0.9)| (40, 0.6) |

with the results reported in [16, 36], where EMD performed very well for the small sample sizes and compact representation but not so well for large sample sizes and wide representation. As indicated in [19], the image size, the number of color features in a signature, and the ground distance may degrade the whole performance of EMD. However, as mentioned before, we only used a signature with 10 color features in this experiment, which is a very compact representation. We note that the large image size of 98,304 pixels or so and the Euclidean ground distance may severely degrade the performance of EMD.

4.3. Dependency on the number of color features in a signature

In general, the quantization level of a color space, that is, the number of clusters in a signature or the number of bins in the fixed histogram, has an important effect on the overall image retrieval performance. In order to investigate the effect of the level of quantization, we examined the performance of the proposed method according to the number of color features in a signature. In this experiment, two quantization levels of 10 and 30 are compared. In addition, the results showed that the mean color error of 30 color features case was 3.38 CIE94 units, which was much smaller than 5.26 CIE94 units, that of the statistical signature with 10 color features. Figures 1(b) and 1(c) show two sample quantized images of Figure 1(a) by 10 and 30 colors, respectively. It is noted that the quantized image with 30 color features is almost indistinguishable from the original image that contains 256,758 color features.

Figure 5 plots the precision-recall curves of the image retrieval results according to the number of color features in a signature. We compared the retrieval performance of the proposed PMHD with EMD, since EMD was the only dissimilarity measure applicable to signatures. The precision rate of EMD did not vary significantly as the number of color features of a signature increased, as depicted in Figure 5. However, the precision rates of PHMD (especially with the Euclidean and CIE94 distances) with 30 color features became higher than that of PMHD with 10 color features. From this result, we can expect that the performance of the proposed PMHD gets better as the quantization error decreases. Moreover, this implies that PMHD performs especially well for the large sample sizes as well as the compact representation.

4.4. Partial matching

In order to assess the performance of the proposed partial PMHD, the same four queries in Figure 3 have been used.
The precision-recall performance has been obtained by varying two parameters, $D_{th}$ and $P_{th}$. Figure 6 plots the best performances and the used parameters are shown in Table 1.

It is noted that although the differences between retrieval performances of two metrics were not significantly large, at most 10% in the case of Eagle, the performance of the partial PMHD mostly outperformed that of full PMHD.

There are some problems in employing the partial PMHD. First, as can be noted in Table 1, it is difficult to get appropriate parameters automatically that can be adopted to all queries. The values of parameters severely depend on the type of query. Second, the performance of the partial PMHD can be more worse than that of the PMHD in high recall rate, as shown in Figure 6(a). Moreover, the complexity of the partial PMHD is a little high compared to that of the PMHD. Thus, in order to exploit the advantages of the partial PMHD for CBIR, these drawbacks should be made up for properly.

5. CONCLUSION

In this paper, we proposed a novel dissimilarity measure for color signatures, perceptually modified Hausdorff distance.
(PMHD) based on Hausdorff distance. PMHD is insensitive to the characteristics changes of mean color features in a signature, and theoretically sound for incorporating human perception in the metric. Also, in order to deal with partial matching, the partial PMHD was defined, which explicitly removed outlier using the outlier detection function.

The extensive experimental results on a real database showed that the proposed PMHD outperformed other conventional dissimilarity measures. The retrieval performance of the PMHD is, on average, 20–30% higher than the second highest one in precision rate. Also the performance of the partial PMHD was tested on the same database. Although there were some unresolved problems including high complexity and finding optimal parameters, the performance of the partial PMHD mostly outperformed that of PMHD and showed great potential for general CBIR applications.

In this paper, we have used only the color information for the signature. However, recent studies showed that combining multiple cues including color, texture, scale, and relevance feedback can improve the results drastically and close the semantic gap. Thus, combining these multiple information in a multiresolution framework will be our future work.
Figure 6: Precision-recall curves for the partial matching: (a) Eagle, (b) Cheetah, (c) Pyramids, and (d) Royal guards.

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Special Issue on
Atypical Speech

Call for Papers

Research in speech processing (e.g., speech coding, speech enhancement, speech recognition, speaker recognition, etc.) tends to concentrate on speech samples collected from normal adult talkers. Focusing only on these “typical speakers” limits the practical applications of automatic speech processing significantly. For instance, a spoken dialogue system should be able to understand any user, even if he or she is under stress or belongs to the elderly population. While there is some research effort in language and gender issues, there remains a critical need for exploring issues related to “atypical speech”. We broadly define atypical speech as speech from speakers with disabilities, children’s speech, speech from the elderly, speech with emotional content, speech in a musical context, and speech recorded through unique, nontraditional transducers. The focus of the issue is on voice quality issues rather than unusual talking styles.

In this call for papers, we aim to concentrate on issues related to processing of atypical speech, issues that are commonly ignored by the mainstream speech processing research. In particular, we solicit original, previously unpublished research on:

- Identification of vocal effort, stress, and emotion in speech
- Identification and classification of speech and voice disorders
- Effects of ill health on speech
- Enhancement of disordered speech
- Processing of children’s speech
- Processing of speech from elderly speakers
- Song and singer identification
- Whispered, screamed, and masked speech
- Novel transduction mechanisms for speech processing
- Computer-based diagnostic and training systems for speech dysfunctions
- Practical applications

Authors should follow the EURASIP Journal on Audio, Speech, and Music Processing manuscript format described at the journal site http://www.hindawi.com/journals/asmp/. Prospective authors should submit an electronic copy of their complete manuscript through the journal Manuscript Tracking System at http://mts.hindawi.com/, according to the following timetable:

| Time Period                      | Date       |
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| Manuscript Due                  | April 1, 2009 |
| First Round of Reviews          | July 1, 2009 |
| Publication Date                | October 1, 2009 |

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The continuous evolution of CMOS technologies, and its variants HV MOS, BCD, and RF CMOS, has enabled the integration of complex functionalities in a single heterogeneous embedded system. Digital subsystems can be integrated onto the same chip or the same package together with RF blocks, analog circuits, power drivers, and even micromechanical parts for sensors and actuators. Such new generation of mixed-signal embedded systems is fueling the development of more efficient and performing solutions in several technology areas: sensors, lab-on-chip, and body area networks for health care; distributed control sensing actuation units for increasing safety, comfort, and engine efficiency in vehicles; software-defined and cognitive radios for multimode multimedia communication; wireless sensor/actuator networks for ambient intelligence.

The opportunity given by mixed-signal embedded systems comes with lots of challenges. The main issues concern the development of innovative methods, languages, CAD tools, and architectures needed in different design phases: high-level specification and simulation, design space exploration to find optimal partitioning between hardware/software and analog/digital functions; codesign of the different subsystems; automatic synthesis; design flexibility and programmability, IP block reuse, and on field reconfigurability; verification and test of mixed-signal components by means of simulations, formal methods, and rapid prototyping; assembly and integration of heterogeneous blocks in the same chip or package.

This Special Issue intends to also address case studies, in the above-mentioned technology areas, demonstrating how the use of mixed-signal embedded systems enables new services/applications or increases the performance and efficiency of existing ones. Authors working in the area of mixed-signal embedded systems are requested to submit original papers or high-quality review articles addressing recent advances in the field. If the work has been published in conference proceedings, the authors should submit an extended version. The topics include, but are not limited to:

- High-performance ADCs and DACs
- Digital calibration/correction of analog and RF circuits in embedded systems with wireless connectivity
- Integration of MEMS, analog, and digital circuits in smart embedded sensors
- Digital and power integration for smart actuators
- Methods for the design of space exploration of mixed-signal architectures and partitioning between hardware/software and analog/digital domains
- CAD tools and languages for mixed-signal embedded systems
- Rapid prototyping techniques and test beds for mixed-signal embedded systems
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Call for Papers

The 2009 European Signal Processing Conference (EUSIPCO-2009) is the seventeenth in a series of conferences organised by the European Association for Signal, Speech, and Image Processing (EURASIP, www.eurasip.org). The conference will be held in the Royal Concert Hall in the heart of the city of Glasgow, Scotland. EUSIPCO-2009 will focus on key aspects of signal processing theory, algorithms, architectures, and applications. Acceptance of submissions will be based on quality, relevance, and originality, with awards for the best student submissions. Accepted papers will be published in the proceedings of EUSIPCO 2009 and presented during the conference. Proposals for tutorials and special sessions are invited. The conference will further include a series of keynote and plenary talks, as well as a CEO forum and exhibition.

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| Electronic submission of full papers | February 6, 2009 |
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