Contact-free hand biometric system for real environments based on geometric features

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1. Introduction

The Biometrics plays an increasingly important part in authentication and identification systems. The processes of biometric recognition allow the identification of individual based on the physical or behavioral characteristics. Various technologies were developed such as fingerprint, iris, face, voice, signature and hand. This last method is based on a study of hand shape and texture. It has many advantages compared to other technologies. Firstly, the capture device is less expensive than that for iris recognition, the hand characteristics are more numerous than those of fingerprints and they can be specified with low resolution images. Moreover, this system is well accepted by users (Jain et al., 2001).
Most of the existing hand involved techniques require pegs or contact-based image acquisition devices. This causes some increasing user acceptance issues and system reliability issues. In this paper we propose a contact-free biometric system based on the hand geometry.
A contact-free system is composed by a pc and a camera. The users put the hand in the free space in front of the camera. In these systems there are two main tasks to solve: the segmentation problems associated to a real environment and the projective distortions associated to the absence of contact plane.
Working with non controlled backgrounds and illumination conditions, the segmentation is not an obvious task. We propose the use of infrared illumination to solve the segmentation problem. The uses of templates guide the user to minimize the projective distortions.
So, in the next section we will review the hand based biometric technology, in order to locate our development in the biometric area. Afterwards we will describe our proposal: segmentation in section 3, the extraction of geometric features will be described in sections 4. Section 5 describes the verification scheme and Section 6 gives our experimental results. The paper is closed with conclusions and the references.

2. State of the art

Traditionally, hand geometry technology is based on analysis of the shape of a hand. The shape has been exclusively characterized by either its geometric sizes or the contour of the hand, or sometimes both. The geometric sizes include measurements of lengths and widths of the fingers, thickness of the fingers and palm, and widths of the palm, etc. A hand contour is formed either by the boundary of the entire hand or by the boundaries of the fingers. In recent research works, (Tantachun et al., 2006) represent a hand pattern by an eigenhand obtained from principle component analysis (PCA) or a mesh constructed from feature points. Accordingly, various techniques have been proposed to obtain and mathematically represent these hand features (Zheng et al., 2007).

Intuitively, geometric sizes of some particular regions of a hand should be used for the hand geometry biometrics. For that purpose, the regions being measured should be the same for each hand each time. This requires a hand to be placed on the exactly the same position on the measuring device. This is accomplished by some guiding pegs mounted on a flat surface of the imaging device. (Jain et al., 1999) developed such a hand geometry authentication system. Five pegs were used to guide the placement of a hand. Both top view and side view images of a hand were taken. Various geometric sizes, including widths, lengths, and thicknesses of fingers, as well as the widths of the palm at different positions were measured. With 16 geometric sizes of a hand, an equal error rate (EER) of 6% was reported. (Sanchez-Reillo et al., 2000) used six pegs in their hand geometry implementation. They measured 25 geometrical sizes of a hand, including widths of fingers and the palm, thicknesses, deviations of fingers, and angles created by the valley points. They obtained an EER less than 3%.

Although the guiding pegs provide consistent measuring positions, they cause some problems as well:

1) The pegs can deform the shape of a hand in which the performance of both size-based and contour-based hand geometry largely relies on. The deformation of hand shapes can increase the variation between hand images of the same hand, which results in false identification [7].

2) The pegs add more complexity to the device. Both the system supervisors and the users must be well trained to cooperate with the system. This increases the responsibility of the users; therefore degrading the reliability of the system.

3) The contact-based devices are becoming an issue due to hygiene and public-health concerns.

Therefore, size-based peg-free hand geometry techniques were under consideration. A typical peg-free hand geometry technique uses optical devices, such as an optical scanner, to capture the images of a hand. The removal of the pegs gives the hand, some motion freedom. To overcome the inconsistent positions of a hand due to the hand motion, the finger tip points and the finger valley points were commonly used as the landmark points for image alignment. (Wong & Shi, 2002) proposed a peg-free hand geometry authentication system using a flatbed optical scanner for hand image capturing. The hand sizes and shape of the fingertip regions were measured. They achieved a genuine acceptance rate of 88.9% and a false acceptance rate (FAR) of 2.2% with 30 hand features. (Bulatov et al.,2004) measured 30 geometric sizes on a hand image. Circles were fitted into different areas of fingers and the palm. The radiuses, perimeters, and areas of the circles, together with the lengths and widths of fingers, were measured. They achieved an FAR of 1% and a false rejection rate (FRR) of 3% for verification. (Boreki & Zimmer, 2005) and (Hashemi & Fatemizadeh, 2005) measured the lengths and widths of each individual finger as well. Boreki et al. profiled curvatures along the hand contour and found landmark points to separate each finger. An FAR of 0.8% and FRR of 3.8% were reported based on 360 images

of 80 users. Heshemi and Fatemizadeh separated each finger from the palm using the distances from the hand contour to a fixed point. In other research efforts, researchers were trying to combine the geometric sizes with other recognition methods, such as palmprint (Wei et al., 2005), hand contour (Oden et al., 2003), or neural-network classifiers (Faundez, 2005) in order to improve system performance.
After trying to remove the effect of the guiding pegs, contact-free hand geometry techniques were also attempted by researchers. (Haeger, 2003) exhibited his work in a project presentation at University of South Florida. In this work, hand images were taken in a free space by a digital camera. The centroid of a segmented hand was detected. A number of concentric circles were drawn around the centroid passing through the fingers. Then different sizes of the fingers were measured by these circles. Using 124 geometric sizes of the fingers, they reached a 45.7% genuine matching rate and 8.6% false matching rate. The poor performance mainly resulted from the hand motions in a free space. Slight changes of viewpoint could tremendously ruin the hand shape.
Several other research works used different ways to create hand descriptors. (Garrison et al., 2001) developed a peg-free and contact-free hand-based authentication system. Hand images were taken using a digital camera from a distance. An eigenhand created by PCA was used as the identifier. But this method suffers from the viewpoint changing due to the perspective distortion on the hand shape. (Doi & Yamanaka, 2003) created a mesh on a hand image captured by an infrared CCD camera. The mesh was created by 20 to 30 feature points extracted from the principal creases of fingers and the palm. Root-mean-square (rms) deviation was used to measure the alignment distance between the meshes. This method is sensitive to the perspective distortion too. (Zheng et al., 2007) present an invariant hand features for contact-free hand biometric systems. An EER of 0% was reported on 52 hand images in a non real environment.
In previous works (Morales et al., 2008), we shows different prototypes based in contact-free hand biometric systems. Using laboratory databases the error rates obtained encourage us to continue the research. In this paper we present our experience working with contact-free systems in real environments.

3. Segmentation

We work with a video sequence and fast background segmentation is important. Usually there are two different video segmentation approaches, shot-based segmentation that uses a set of key-frames to represent a video shot and object-based segmentation that partitions a video shot into objects and background (Lijie & Guoliang, 2005). We use an object-based segmentation because the user hand is in close-up. The uses of direct illumination give the necessary contrast between hand and background. The segmentation problem is not obvious working in real environments.
We tried to use face detection techniques for solve the hand segmentation problem. The most common techniques are the skin based methods (Ruiz & Verschae, 2004). Skin detection is not robust enough for dealing with complex environments. Changing lighting conditions, and complex background containing surfaces and objects with skin-like colors are major problems, limiting its use in practical "real world" applications.
In a real application without controlled illumination and unknown background, the segmentation is not a trivial problem. In the beginning, the webcam was used with a

lighting system composed for a standard bulb of 60W that emits in the visible light range. The system was placed at a vertical position and the right hand palm had to be placed at about 30 cm of the system, facing the web-cam.

After a study of the captured hands, it was observed that the system performance decreased in the following situations:

1) when direct light fell in the web-camera lens.
2) with a non uniform background.
3) when there was an object in close-up.
4) when there was a reflection object in the background.

The decreasing of the system performance was due to segmentation problems, being impossible to extract the hand from background. Therefore, the performance of the verification process was not enough good because for a correct verification a good segmentation is needed.

Before discard the skin segmentation techniques, we studied the infra-red illumination. With a correct illumination, the problem of segmentation can be solved. In the Fig. 1.a we can see an example of a captured image in a real non controlled environment. The background segmentation is a hard task with this kind of environment. In the Fig. 1.b we can see the problems to use the skin segmentation methods with two near skin objects. A solution to this problem was proposed. Use infra-red illumination. The visible light system was replaced for an infrared system.

To obtain an adequate image acquisition, the web-cam specifications have to be set in this way: maximum contrast and brightness with a low value to achieve a very high contrast between hand and background, low gain and exposure to enhance the close-up. The low exposure is important in order to eliminate the background. We can see an example in the Fig. 1.c. The Fig. 1.d shows the near skin objects example.

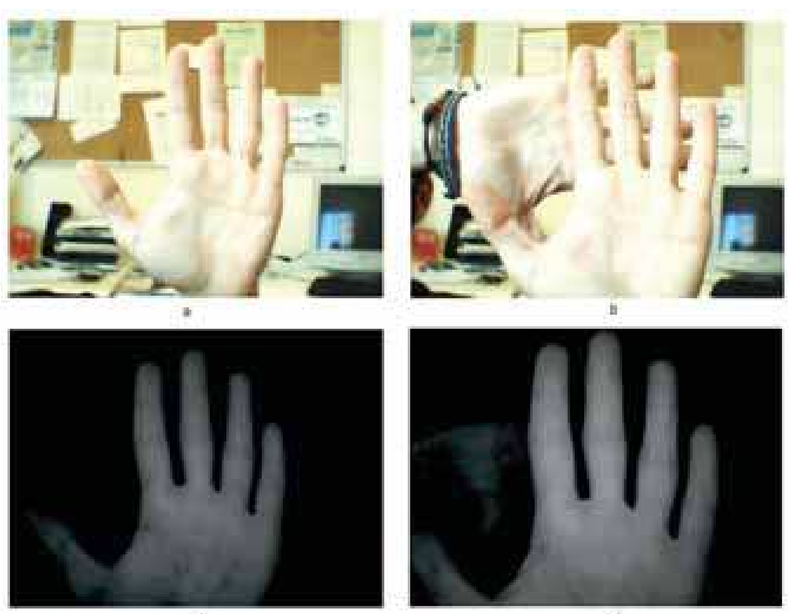

Fig. 1. a) Captured image in visible range; b) Near skin objects in visible range; c) Image a in infrared domain; d) Image b in infrared domain

This system is composed for a set of GaAs infrared emitting diode (CQY 99) with a peak wavelength emission of 925 nm and a spectral half bandwidth of 40 nm. The diodes were placed in an inverted U shape with the webcam in the middle. The number of diodes used is 16 and the current is 110 mA for each diode pair. The user can observe the correct positioning in a 12'' screen.

Fig. 2. System prototype

The web-cam was modified in order to adapt it to receive infrared emissions: the infrared filter was removed (normal in the commercial webcams) and two cascade filters were added. The added filters are Kodak No 87 FS4-518 and No 87c FS4-519 visible opaque infrared filters, with no transmittance between 400-700 nm.
The user in our system can place the hand palm freely in the 3D space in front of the camera. We do not use surface, the system is contact-free. We use a template for a correct positioning of the hands to reduce the projective distortions associated to the absence of contact plane, see Fig. 3.

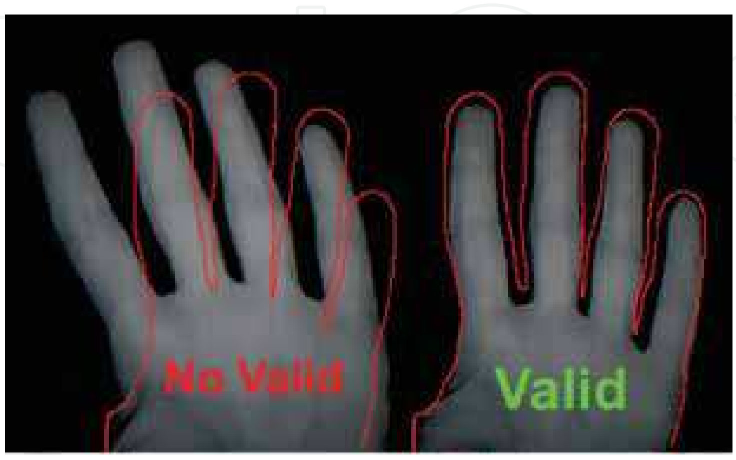

Fig. 3. Template and hand positioning

Once obtained the infrared image, the segmentation is simple. We use a low-pass filter to obtain the binary image from the gray scale IR image. This is a fast method in computational terms. The filter uses two-dimensional Hamming window to form an approximately circularly symmetric window using Huang's method. The cut frequencies are $\omega_1 = \pi$ all pass filter and $\omega_2 = 0.5\pi$ low-pass filter. This filter enhances the vertical lines to improve the contrast between hand and background.
The filtered image is normalized in amplitude and binarized by the Otsu's method. This method chooses the threshold to minimize the intraclass variance of the thresholded black and white pixels. Once we apply the binarization, we obtain hand image in white colour and background in black.
The last step is performing of a flood-fill operation on the binary image to fill small hand holes that can appear in the binarization phase.

4. Parameterization

The hand's contour is obtained from the black and white image. To work out the ends and valleys between the fingers we convert the Cartesian coordinates of the hand contour to polar coordinates (radius and angle) considering as coordinates origin the center of the hand base. The peaks of the radius locate the finger ends and the minimums of the radius indicate the valleys between fingers.
To obtain the exterior base of the index and little finger, we work out the slope of the line going from the index-heart fingers valley to the ring-little fingers valley (Ferrer et al., 2007). The exterior of the thumb is worked out as the intersection of the contour and the line going from the heart-ring fingers valley to the index-thumb fingers valley.
Once located the most important points of the hand, we can obtain the geometric features by means of measures. We use the geometrical features of the little, the index, middle and ring fingers, see Fig. 4. The reason for no uses the thumb finger is the great variance of the positioning in this finger.

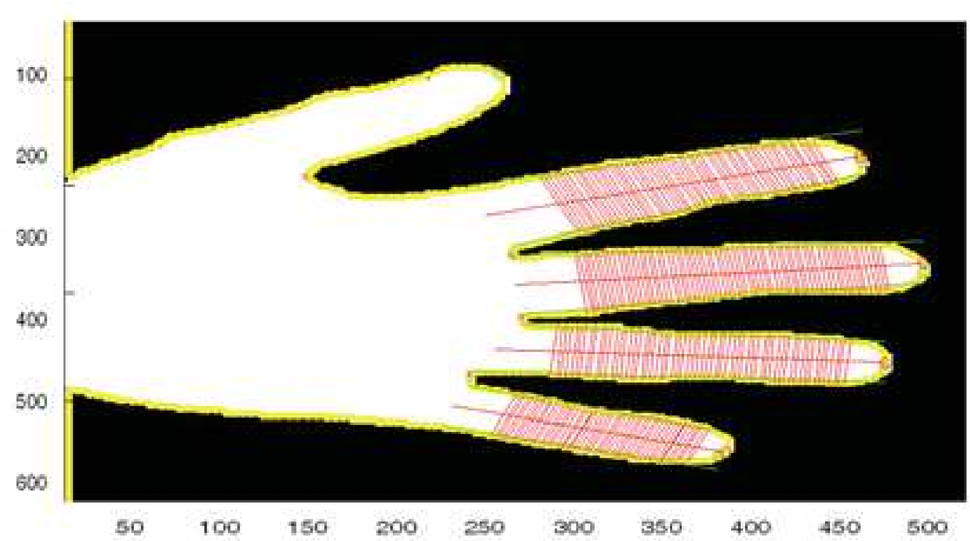

Fig. 4. Feature extraction

To obtain the geometric feature vector is immediate once the ends and valleys between fingers have been detected. Each finger is characterized as a triangle. The three vertexes of the triangle are the end and the two side valleys of the finger. We take approximately 60 wide measures to parameterize the little, the index, middle and ring fingers. We discard the first 20% of the finger to solve rings problems. Each hand is characterized by 240 measures vector.
The Fig. 5 shows ten parameter vectors for two different users, five acquisition for each user. The geometric features are normalized. We can observe the inter-class and intra-class variance.

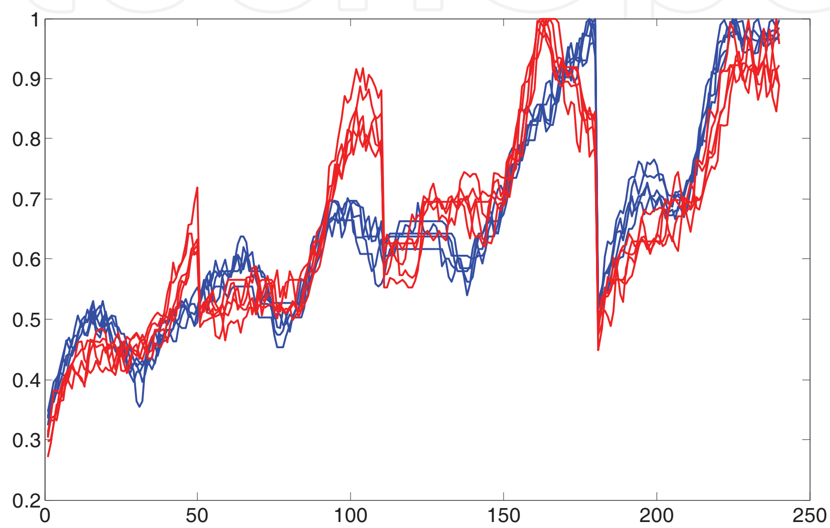

Fig. 5. Intra-class and inter-class variance example

In a contact-free system, the user can put the hand freely in a 3D space. To minimize the intra-class variance produced by the projective distortions we applied the DCT transform, equation 1.

$$DCT(u,v) = \frac{1}{\sqrt{2n}} C(u)C(v) \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} f(x,y) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cdot \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

$$C(u), C(v) = \begin{cases} \frac{1}{\sqrt{2}} & u,v=0 \\ 1 & rest \end{cases} \qquad u,v = 0,1,\ldots,N-1 \tag{1}$$

Where *f(x,y)* is the array of N original values and *DCT(u,v)* are the DCT coefficients. We use the first 45 coefficients to characterize each hand. In Fig 6, we can observe the transformed vectors obtained from exaples showed in previous figures.

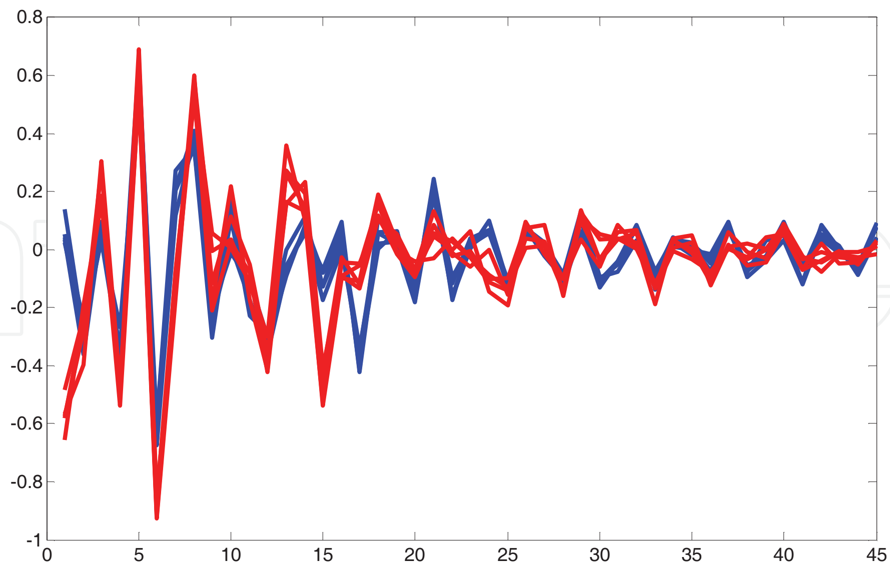

Fig. 6. DCT transform of geometric features

5. Verification

During four months, 102 people (70 genuine and 32 impostors) use the system. More than 900 unsupervised accesses were achieved. The total of the images have been taken from the user's right hand. Most of the users are within a selective age range from 21 to 33 years old. In the database, 63% of the users are males. The database was acquired in "Real World" conditions. No supervised and non controlled environments conditions.
The verification scheme depends on the feature vector. We have used a support vector machine (SVM) for classify the features. We have used for modeling the geometric hand features the technique of Support Vector Machines (SVM) because it generally provides better generalization performance. SVM learning machine seeks for an optimal separating hyperplane between classes. In order to achieve a good level of generalization performance, we maximize the margin between the separator hyperplane and the data.
The software used to train and test the model is the LS-SVM[24]. To verify that an input hand belongs to the identity claimed, we calculate the distance of the input hand features to the separator hyperplane of the SVM that model the hands of the identity claimed. If the distance is greater than a threshold, the identity is accepted.

6. Experiments

Four hands were used for train, the rest were used for test purpose. Fig.7 presents the False Acceptance Rate versus the False Rejection Rate. The Equal Error Rate is the point where the two error rates are equals.

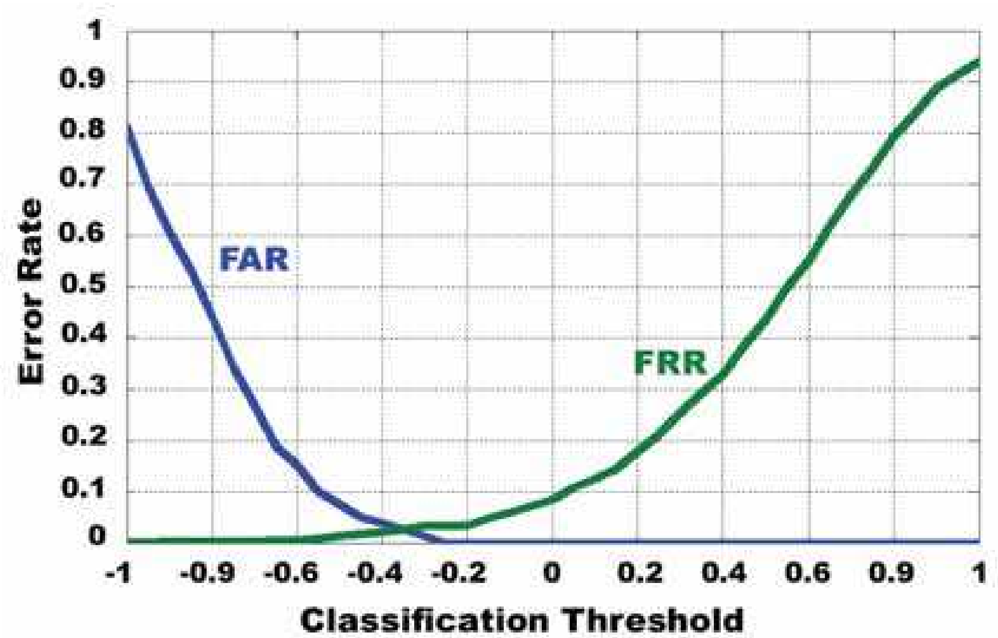

Fig. 7. FAR and FRR results

7. Conclusions

This chapter has presented a contact-free biometric identification system based on the geometrical hand features. A "real world" database, composed by 102 users and more than 4000 images was used. The results reports an EER of 3.2% encourage to us to follow the present research. With the segmentation problem solved, we should to improve the parameterization methods. Minimize the projective distortions associates to the contact-free biometric systems and elaborate a more extensive database will be the principal tasks.

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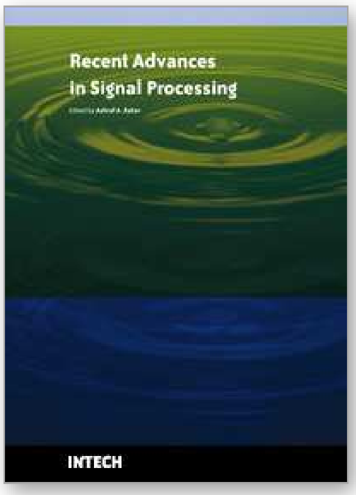

Recent Advances in Signal Processing

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The signal processing task is a very critical issue in the majority of new technological inventions and challenges in a variety of applications in both science and engineering fields. Classical signal processing techniques have largely worked with mathematical models that are linear, local, stationary, and Gaussian. They have always favored closed-form tractability over real-world accuracy. These constraints were imposed by the lack of powerful computing tools. During the last few decades, signal processing theories, developments, and applications have matured rapidly and now include tools from many areas of mathematics, computer science, physics, and engineering. This book is targeted primarily toward both students and researchers who want to be exposed to a wide variety of signal processing techniques and algorithms. It includes 27 chapters that can be categorized into five different areas depending on the application at hand. These five categories are ordered to address image processing, speech processing, communication systems, time-series analysis, and educational packages respectively. The book has the advantage of providing a collection of applications that are completely independent and self-contained; thus, the interested reader can choose any chapter and skip to another without losing continuity.