Users Verification Based on Palm-Prints and Hand Geometry with Hidden Markov Models

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Abstract. This paper presents a biometric system implementing identity verification on the basis of the geometry of a hand and palm-prints. Hidden Markov Models were used here as teaching and verifying tools. The paper includes suggestions of our own algorithms as well as hand features extraction methods and their specific coding for Hidden Markov Models. The obtained results show that human hand carries a lot of useful information and appropriately modified can become an interesting proposal among biometric systems, particularly carrying out the verification process with a limited number of users.

Keywords: palm-prints, hand geometry, biometrics, verification, HMM.

1 Introduction

People identification is an important problem in many computer systems and electronic systems. The well-known methods of identification, such as entering a PIN number, entering login and password or using the ID cards have many difficulties and disadvantages. It is easy to forget the PIN numbers, passwords, as well as lose identification card. In addition, the card can be stolen and protecting passwords broken. Therefore, the traditional methods of identifying people are becoming less popular. On the other hand biometric methods are gaining vast popularity in identification and verification of people. These methods use the digital measurement of certain physical and behavioral characteristics of humans and compare them with the pattern stored in the database. Until now, many biometric methods which enable identification and verification of people have been developed. From among all of these methods, hand geometry and palm-prints recognition deserves special attention.

Human hands are used as one of the crucial features in people identification. The paper [1] describes a number of features that can be extracted from a hand image and used in the identification or verification of a person. To these features the author includes, inter alia, a hand geometry which consists of measuring height, width and surface of a hand. Next, to the main features the author

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includes palm-prints, wrinkles, which are less regular than fingerprints, minutiae which are similar to the features obtained from fingerprints.

In another paper [2] the author shows the way of identification which is based only on basis metacarpalis. A person is identified on the basis of a hand part which is located between the wrist and the fingers. Image of the hand, as in most of the works of this type, is subjected to the segmentation which is the extraction of palm-prints. In the following work over the image, the author uses Gabor filters to obtain a more accurate frame of the palm-prints. The final step is to compare the image in the database with the received image of the hand. Studies were conducted on about 200 people. There were taken 20 pictures of left and 20 pictures of right hand of each person participating in the studies. A rejection rate of entitled person was only FRR=3%, and FAR rate=0.1%.

One of the oldest biometric techniques is a geometric measurement of the hand. This method involves typical features like the length of fingers and base of a hand, width of fingers in certain places, thickness of fingers and hands, and lines between fingers. Information about the shape of a hand are calculated on the basis of hand picture. The standard device for geometric measurement of a hand consists of a closed-circuit television camera, an infrared floodlight and a special plate which is equipped with five rings for hand positioning. The system automatically checks the correct hand position on the plate, if it is correct it takes a picture. In addition, the plate is equipped with two small mirrors in order to receive the image of a hand and thumb edges.

After taking the picture, different techniques are used for image processing and determination of the hand geometric features [3]. In some publications we can find various lists of features. For example in paper [4], the author suggests a list of 25 features with 10 teaching images for each person. The database includes 20 people. For determination of the palm features is used normal distribution - Gaussian distribution. On the other hand the authors of the paper [5] suggested a set of 16 geometrical features of hands. The set includes width and length of fingers, the ratio of size of the hand base and fingers, as well as thickness of the hand. For working over the image they used Euclidean and Mahalanobis method.

The studies of the hand image often differ from each other only in determination of the geometric features. In some papers we may find information that author suggests a set of 25 features and sometimes even 40. Obtained features undergo the process of qualification using conventional methods such as neural networks and stochastic tools. We suggest using hand shape analysis combined with palm-prints analysis to verify the identity of people. The Hidden Markov Models will be applied as a teaching-verifying tool.

2 Detection of Characteristic Hand Features

Prior to building the system that performs identity verification based on features provided by hand picture it is necessary to determine in what conditions and in what environment the system will work. For the analysis of hand shape may be used a specially prepared plate with pins placed on the surface of it. The pins should provide the same arrangements on the plate for each of analyzed hands, which at a later stage would greatly facilitate the process of measuring geometric features of a hand. Additionally if an information on palm-prints will be required apart from the hand shape, then the arrangement of a hand on the plate will depend on a type of device receiving the image.

The obtained hand image must undergo the indispensable pretreatment processes in order to adjust the image to the requirements of the measurement procedure of geometric features. First, detection of a hand in the image is performed. It is obvious that the hand picture was taken on a specially prepared plate of uniform surface colour, different from the hand colour. Thresholding can be done by cutting out the surface colour from the image and replacing it with e.g. black colour (for monochrome pictures), or by a specific skin colour (for colour pictures).

The determined area of the hand easily enables further analysis of its geometric features, including accurate measurement of each analyzed hand. Because special pins are placed on the plate, it is sufficient to take the distance between any pins as a reference point of dimension, which allows to automatically scale the image to identical actual sizes, regardless of the distance from the camera. The proceedings pattern during the measurement of the hand geometry and setting the limited hand area are shown in Fig. 1.

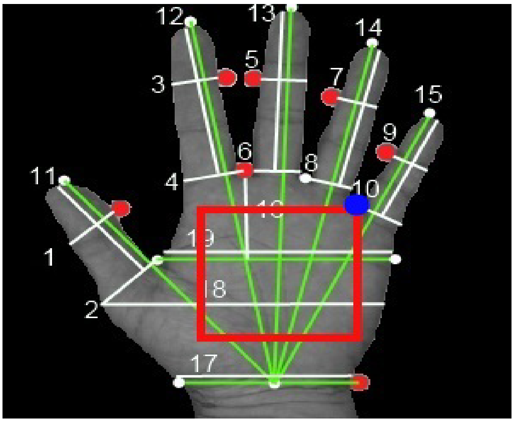

Fig. 1. The method of geometric measurement of hand features

On the basis of pins placed on the plate (marked in red in the picture) it is possible to detect additional points needed for assumed measurements (white dots). It is performed in the following way, for example, a thumb is searched for the maximum non-zero pixel (not black) to the left of the pin and the minimum non-zero pixel to the right of the pin. For the other fingers, the method is very similar. The points characterizing beginnings and ends of fingers are marked in this way. The last thing to do is to designate points which characterize width of a hand and wrist and half the width of the wrist. For this purpose the auxiliary lines are drawn (green) parallel to the edge of the photo from the pin placed at the wrist and from the minimum point on the right side of the thumb. The intersection of the auxiliary lines and the hand edge designates the remaining points. Auxiliary lines are also drawn from the fingertips to the point which indicates half the width of the wrist (also green). The prepared frame of auxiliary lines will allow to make further measurements.

Determination of the sizes is based on the assumption that the measurements are carried out in directions perpendicular to the auxiliary lines at the designated characteristic points. In this way determined are: the width of a thumb (distance 1 and 2) and the length of a thumb (distance 11), the width of an index finger (distance 3 and 4) and the length of an index finger (distance 12), the width of a middle finger (distance 5 and 6) and the length of a middle finger (distance 13), the width of a ring finger (distance 7 and 8) and the length of a ring finger (distance 14), the width of a small finger (distance 9 and 10) and the length of a small finger (distance 15), the distance between the base pin and line 19 characterizing the width of a hand (distance 16), the width of a wrist (distance 17), the width of a hand (distance 18 and 19). Nineteen different distances characterizing geometric features of analyzed hand are designated in this way. Due to the fact that the distance between the leading pins located between index finger and middle finger is exactly 10 millimeters, all determined distances can also be reported in millimeters.

Since there is a possibility of measuring geometric features of a hand in a millimeter scale, it is possible each time to mark out e.g. a square or rectangular area of pre-defined dimensions. The reference point may be the end of a ring finger and a small finger (see Fig. 1).

Searching for simplicity in proceedings, and thus accepting only the main palm-prints analysis, an interesting solution could be the use of a simple directional edge detector. With the appropriate settings of detector coefficients it is possible to omit little, short, faint lines. However, there is a problem because such a clearly visible hand line will have designated edges on both its sides, which does not facilitate further work. However, at this time we can use a morphological operation - dilatation, which will connect the separate edge lines.

Dilatation greatly increases the thickness of lines, but the shape and location of major palm-prints is not changed. In order to interchangeably define the palm-prints shapes, these bold elements should be brought closer by one pixel thick lines. This can be done by using the linear Hough transform. The transform allows the detection of the straight lines in binary image. With appropriate parameters (the minimum length of searched palm-prints should be adjusted) the output effect of Hough transform will be the whole family of lines gathered around the bold palm-prints. Taking into account the distribution of nodes in the Hough space, we select only those lines which nodes are arranged in a continuous and intense way. Palm-prints which are selected in this way are also defined with an approximating line. Fig. 2 illustrates the effect of designating major palm-prints with the usage of the linear Hough transform.

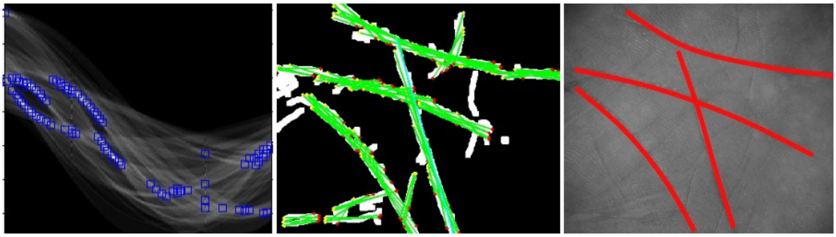

Fig. 2. Designated space of Hough transform on the left, applied operation of lines detection on the basis of the transform in the middle and approximation operation on the right

3 Coding of Appointed Features for Hidden Markov Models

Coding of hand features is connected with determining the way of procedure with each hand feature. First from appointed features concerns the geometric shapes of the hand. Forming of the observation vector is combined with giving consecutive geometric dimensions which are calculated for each finger and the whole hand. Calculated 19 dimensions in millimetres are contained in the range of the whole numbers from a to b. The observation vector will be composed of other dimensions. It will allow to distinguish the two hands of similar shapes but different in sizes.

Coding of palm-prints of the hand can be executed starting from dividing the input image into a fixed number of square sub-images. At this work the size of image consisting of palm-prints is 60 x 60 mm. At these values the input image can be divided into 144 sub-images.

Each sub-image has one observation symbol. Coding of palm-prints consists in the choice of only these sub-images which consist any of fixed palm-prints. Forming the observation vector the sub-images are chosen according to approved numeration. If a given sub-image consists a line, then besides the number of sub-image, in the observation vector the information about the average angle where a given piece of a line is arranged relative to the horizontal axis. In order to limit the observation symbols connected with coding the angles, defined between palm-prints and the horizontal axis, the division of semi-circle (180^o) is accepted to a fixed number of slices (e.g. 16). In such a way for every angle one of 16 observation values are assigned. The scheme of such coding is shown in Fig. 3. Based on the above mentioned scheme, the sample observation vector begins from the third value for which the angle code is 13, the next observation is 16-th value with the angle code 13, and in conse-quence the next is 17-th with the angle code 14, etc. If in the given sub-image there are two or more lines, then besides the number of an observed sub-area, the angle codes of all lines are assigned (starting from the lowest lines). The resultant angle is assigned on the basis of a tangent to a curve (describing the palm print) in points P1 (the beginning of the line), P2

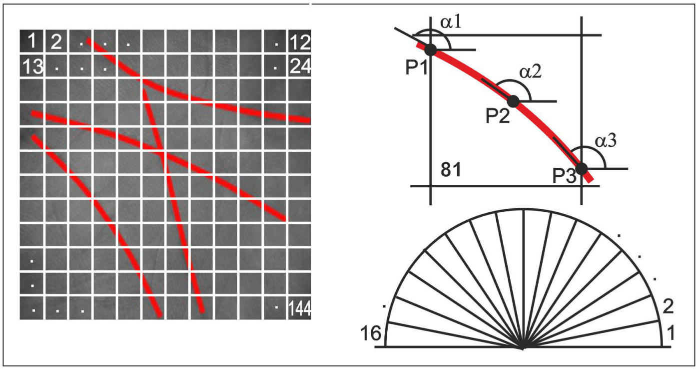

Fig. 3. The scheme of procedure during assigning the observation vectors using this coding method

(the middle of the line) and P3 (the end of the line) within a given sub-image. In the next steps the average angle is determined from the angles $\alpha1$, $\alpha2$ and $\alpha3$.

The presented way of coding assumes the possibility of erroneous detection of main palm-prints, which determines an incomplete line or its entire omission. The essential element in such a way of coding is the acceptable variable number of observation which in case of vector measurement using the distance method, would introduce the complement of vector size (e.g. unities, zeros), causing too much similitude of data. Using the teaching-verifying tool in the case of Hidden Markov Models, the possibility of generalizing the patterns is kept, despite rapidly changing observation vectors of certain characteristics of the image.

4 The Use of Hidden Markov Models

The Hidden Markov Model (HMM) is a powerful statistical tool for modeling generative sequences that can be characterised by an underlying process generating an observable sequence. HMMs have found application in many areas interested in signal processing, and in particular speech processing, but have also been applied with success to low level natural language processing tasks such as part of speech tagging, phrase chunking, and extracting target information from documents. HMMs are stochastic models and are widely used for characterizing the spectral properties of frames of patterns [6–11].

A HMM is characterized by: the number of states in the model N, the number of Gaussian mixtures per state M, the state transition probability distribution A, the observation symbol probability distribution B, and the initial state distribution π. The compact notation $\lambda = (A, B, \pi)$ is used to indicate the complete parameter set of an HMM model.

HMMs have three fundamental problems, namely recognition, segmentation and trying. These problems can be defined as follows: 1) recognition problem is computing the probability $P(O|\lambda)$ given the observation sequence O and the model λ, 2) segmentation problem is the determination of the optimal state sequence given the observation sequence $O = O1, O2, , OT$, and the model λ, 3) training problem is the adjustment of model parameters $\lambda = (A, B, \pi)$ so as to best account for the model states, this is equal to adjust the model parameters $\lambda = (A, B, \pi)$ to maximize $P(O|\lambda)$.

Given a HMM, and a sequence of observations, we'd like to be able to compute $P(O|\lambda)$, the probability of the observation sequence given a model. This problem could be viewed as one of evaluating how well a model predicts a given observation sequence, and thus allow us to choose the most appropriate model from a set. The probability of the observations O for a specific state sequence Q is:

$$P(O|Q, \lambda) = \prod_{t=1}^{T} P(o_t|q_t, \lambda) = b_{q1}(o_1) \times b_{q2}(o_2)...b_{qT}(o_T) \tag{1}$$

and the probability of the state sequence is:

$$P(Q|\lambda) = \pi_{q1} a_{q1q2} a_{q2q2} ... a_{qT-1qT} \tag{2}$$

so we can calculate the probability of the observations given the model as:

$$P(Q|\lambda) = \sum_{Q} P(O|Q, \lambda) P(Q|\lambda) = \sum_{q_1 \cdots q_T} \pi_{q_1} b_{q_1}(o_1) a_{q_1 q_2} b_{q_2}(o_2) ... a_{q_{T-1} q_T} b_{q_T}(o_T) \tag{3}$$

This result allows the evaluation of the probability of O, but to evaluate it directly would be exponential in T.

A better approach is to recognise that many redundant calculations would be made by directly evaluating eq. 3, and therefore caching calculations can lead to reduced complexity. We implement the cache as a trellis of states at each time step, calculating the cached valued (called α) for each state as a sum over all states at the previous time step. α is the probability of the partial observation sequence $o_1, o_2, ..., o_t$ and state s_i at time t. We define the forward probability variable:

$$\alpha_t(i) = P(o_1 o_2 ... o_t, q_t = s_i \lambda) \tag{4}$$

so if we work through the trellis filling in the values of α the sum of the final column of the trellis will equal the probability of the observation sequence. The algorithm for this process is called the forward algorithm and is as follows: Initialisation:

$$\alpha_1(i) = \pi_i b_i(o_1), 1 \leq i \leq N \tag{5}$$

Induction:

$$\alpha_{t+1}(j) = [\sum_{i=1}^{N} \alpha_t(i) a_{ij}] b_j(o_{t+1}), 1 \leq t \leq T-1, 1 \leq j \leq N \tag{6}$$

Termination:

$$P(Q|\lambda) = \sum_{i=1}^{N} \alpha_T(i) \tag{7}$$

For each state s_j, $\alpha_j(t)$ stores the probability of arriving in that state having observed the observation sequence up until time t.

It is apparent that by caching α values the forward algorithm reduces the complexity of calculations involved to N^2T rather than $2TN^T$. We can also define an analogous backwards algorithm which is the exact reverse of the forwards algorithm with the backwards variable:

$$\beta_t(i) = P(o_{t+1}o_{t+2}...o_T|q_t = s_i, \lambda) \tag{8}$$

as the probability of the partial observation sequence from $t + 1$ to T, starting in state s_i [7].

5 Experimental Results

The research to determine the effectiveness of the identity verification on the basis of the hand shape and main palm-prints are conducted for the usefulness of Hidden Markov Models also to such biometric systems. The hand geometry provides 19 different dimensions describing the shape of a given user. If the identity verification is on the basis of the hand shape, then the comparative method is enough to estimate the distance between two compared vector features.

The first of the research connected with the human hands is to determine the correctness of the identity verification on the basis of hand geometry. The study was to determine the false rejection rate and the false acceptance rate for different number of analysed users. 500 different users were tested for whom 2 photos were downloaded (first for the registration and second for testing). The error rates were determined for 100, 200, 300, 400 and 500 users. All pictures which form input data were taken in the same conditions and using the same equipment. The results of errors are in the Table. 1. The further tests concerned the influence of the use of Hidden Markov Models on the quality of identity verification. The way of connecting hand features provided by the shape and by the main palm-prints are considered. It is not easy to choose the ideal method based on the characteristics which while having a lot of users show quite a similarity. The twofold way of verification was presented. First one was based on the use of Hidden Markov Models only to analysis of the palm-prints, the shape features were left to vector comparison. The second way accepted both the geometric characteristics and palm-prints characteristics as the input data during forming of the observation vector. In the first case the correct verification required the proper answer from the camera which compares the distance between vectors and the camera which carries out the recognition. Only mutual compatibility designs the correct verification. The results of this verification are in the Table. 2, where the error rates are determined using the number of users of 100, 200, 300, 400 and 500. Better solution is to allow for the geometric hand features during forming of the observation vectors given on the input models during teaching and verifying. The more distinguishable features are provided to the model the better results are. Of course the correctness of assigning and coding of input data is important. In the Table. 3 there are the results of assigning the errors during user

Table 1. Results of tests for identity verification based on the geometry of the hand

Tests	Num. of Users	Num. of FA	FAR [%]	Num. of FR	FRR [%]
1	100	0	0.00	0	0.00
2	200	1	0.50	4	2.00
3	300	6	2.00	21	7.00
4	400	13	3.25	39	9.75
5	500	26	5.20	73	14.60

Table 2. Results of tests for identity verification based on the geometry of the hand and palmprint with separate HMM

Tests	Num. of Users	Num. of FA	FAR [%]	Num. of FR	FRR [%]
1	100	0	0.00	2	2.00
2	200	0	0.00	7	3.50
3	300	3	1.00	13	4.33
4	400	9	2.25	27	6.75
5	500	16	3.20	55	11.00

Table 3. Results of tests for identity verification based on the geometry of the hand and palmprint with coupled HMM

Tests	Num. of Users	Num. of FA	FAR [%]	Num. of FR	FRR [%]
1	100	0	0.00	0	0.00
2	200	0	0.00	0	0.00
3	300	1	0.33	3	1.00
4	400	4	1.00	7	1.75
5	500	7	1.40	13	2.60

verification, based on combined vector of shape and palm-prints characteristics. The obtained results show the purpose of the use of Hidden Markov Models to increase the effectiveness of biometric system using the verification based on the hand shape and main palm-prints. If in the verification process the use of only geometric features, describing the shape of a hand, with the increase of the user numbers in the database, both the false rejection rate and the false acceptance rate increase to dangerous levels. As far as the false rejection rate for 500 users at 14.6% is only inconvenient for users, the false acceptance rate at over 5% is a serious danger for the system safety.

The use of Hidden Markov Models must have its quality justification. If you assume as input data only the characteristics connected with the image of palm-prints, and geometric features will be compared as usual vector comparison, then the false rejection rate increases in relation to increasing number of users.

If only while forming of vector observation geometric features of hand are taken into consideration then the obtained results confirm the wisdom of the use of Hidden Markov Models to such biometric systems. For 500 users the false acceptance rate at 1.4% is not enough. Also the false rejection rate at 2.6% is not a great hindrance to potential users of the system. For less than 100 users the system is very safe and can be used to secure important resources.

The perfect solution would be to gain the index at 0.0001% however it was not the main purpose of the analysis in this chapter. Taking into consideration the geometric features of a hand seen from above and geometric features of a hand seen from the side and besides main palm-prints, also detailed palm-prints then the system could be formed which would function as the identification system. Most verifying systems based on biometric features are dedicated for the small number of users, so the fulfilling of level of security is not a complicated task. The searching of such solutions is important which at relatively low effort and using useful tools increase the effectiveness of biometric systems [12, 13]. The table of the obtained results of above studies is shown in Fig. 4.

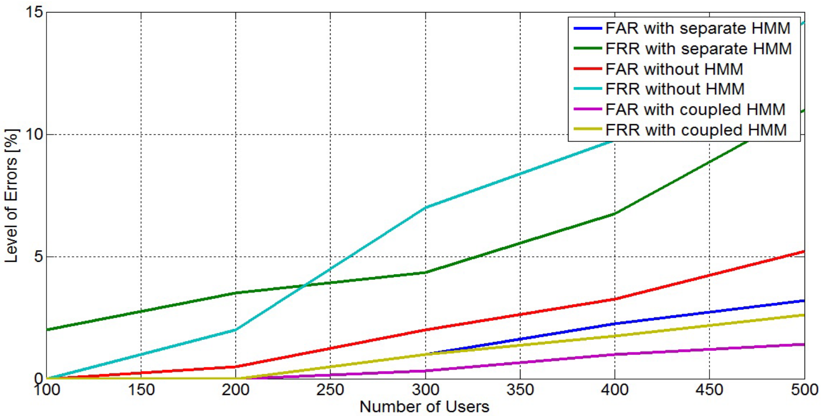

Fig. 4. The graph of dependence of false acceptance rate and false rejection rate on the number of users in the database (without, with separate and combined HMM)

6 Conclusion and Future Work

In this article the biometric system for identity verification is shown on the basis of hand shape and main palm-prints. As the tool which supports the process of verification Hidden Markov Models are presented. Several solutions are proposed connected with the analysis of the image for extraction of searching features and the way of connecting assigned geometric and visual features. The author‘s way of coding of palm-prints was described, developed for the need and possibility of the use of Hidden Markov Models.

Conducted studies show that in case of big number of users the analysis of geometric features gives not enough safety. But if you take into consideration the features given by the picture of the palm then by proper coding it is possible to gain better results.

Further studies will be connected with increasing the effectiveness of biometric system through the expansion of the number of variable characteristics to geometric features provided by the side image of the hand and visual features coming from the detailed palm-prints.

References

1. Shu, W., Zhang, D.: Automated Personal Identification by Palmprint. Optical Engineering 37, 2359–2362 (1998)
2. Fatric, I., Ribaric, S.: Colour-Based Palmprint Verification – An Experiment. In: Watteyne, T., Yazidi, A. (eds.) The 14th IEEE Mediterranean Electrotechnical Conference Proceedings, pp. 890–895. IEEE, Ajaccio (2008)
3. Guo, J., Liu, Y., Yuan, W.: Palmprint Recognition Using Block Entropy Map From a Single Image Per Person. Journal of Computational Information Systems 8(12), 5129–5135 (2012)
4. Sanches-Reillo, R., Sanchez-Avila, C., Gonzalez-Marcos, A.: Biometric Identification through Hand Geometry Measurements. IEEE Transactions on Pattern Analysis and Machine Intelligence 22(10), 1168–1171 (2000)
5. Jain, A.K., Ross, A., Pankanti, S.: A Prototype Hand Geometry Based Verification System. In: Proc. of 2nd Int. Conference on Audio and Video-Based Biometric Person Authentication, Washington D.C, pp. 166–171 (1999)
6. Rabiner, L., Yuang, B.H.: Fundamentals of Speech Recognition. Prentice Hall Signal Processing Series (1993)
7. Kaynak, M.N.N., Zhi, Q., Cheok, A.D., Sengupta, K., Chung, K.C.: Audio-Visual Modeling for Bimodal Speech Recognition. In: Proc. 2001 International FuzzySystems Conference (2001)
8. Blunsom, P.: Hidden Markov Models, http://digital.cs.usu.edu/~cyan/CS7960/hmm-tutorial.pdf
9. Bobulski, J.: Selection of Parameters of HMM. Measurement, Automation, Control 10, 844–846 (2009)
10. Bobulski, J.: Analysis of 2D Problem in HMM. Methods of Applied Informatics. 4(17), 27–33 (2008)
11. Verma, N.K., Hanmandlu, M.: Additive and Non-additive Fuzzy Hidden Markov Models. IEEE Trans. Fuzzy Systems 18(1), 40–56 (2010)
12. Choras, M., Kozik, R.: Contactless Palmprint and Knuckle Biometrics for Mobile Devices. Pattern Analysis and Applications 15(1), 73–85 (2012)
13. Choraś, M., Kozik, R.: Fast Feature Extractors for Palmprint Biometrics. In: Chaki, N., Cortesi, A., et al. (eds.) CISIM 2011. CCIS, vol. 245, pp. 121–127. Springer, Heidelberg (2011)