The Korean Institute of Communications and Information Sciences

Available online at www.sciencedirect.com

ScienceDirect

ICT Express ▮ (▮▮▮▮) ▮▮▮–▮▮▮

www.elsevier.com/locate/icte

Soft biometrics through hand gestures driven by visual stimuli

Nahumi Nugrahaningsih[a], Marco Porta[b,*]

[a] Department of Informatics, University of Palangkaraya, Palangkaraya, Indonesia
[b] Dip. di Ingegneria Industriale e dell'Informazione, Università di Pavia, Pavia, Italy

Received 21 November 2017; received in revised form 4 March 2018; accepted 25 April 2018
Available online xxxx

Abstract

We present a novel biometric solution which exploits hand gestures, tracked by the Microsoft Kinect sensor, performed in response to a circle randomly appearing in five predefined screen positions. Features of both hand and screen pointer are used for classification purposes, considering both the whole 20-path trajectory and shorter routes. In particular, we search for the "optimal" trajectory length which assures a good trade-off between precision and user effort. For identification, the approach achieves classification accuracies ranging from 0.748 to 0.942. For verification, accuracy is still satisfactory (always higher than 0.962), despite moderate specificity values.

Keywords: Soft biometrics; Gestures; Visual stimuli

1. Introduction

Body gestures are an essential part of non-verbal communication, and probably also one of the most natural components of human–human interaction. In several circumstances, gestural languages can be more effective than oral statements (e.g., when the communication occurs at a distance). Therefore, it is not surprising that body gestures are increasingly being considered for biometric applications, both for identification (i.e., recognizing an individual) and for verification (i.e., confirming or denying the claimed identity of an individual).

Among the different kinds of body gestures, those involving the hands are probably the most widespread. Explicit identification and verification based on hand gestures seem therefore viable approaches, either as additional verification mechanisms (besides more traditional techniques such as those exploiting PINs) or when the identity check must take place at a distance (e.g., in environments in which touchless procedures are mandatory).

Gesture-based methods have advantages over other common identification and authentication techniques, as gestures may require lower attention and precision compared to other solutions — while a wrongly entered text password is automatically rejected, some inaccuracy may be tolerated in a gesture code.

Vision-based hand gesture recognition has recently become a relatively easy task thanks to cheap devices such as Microsoft Kinect [1] and Leap Motion [2]. These tools can merge 2D and 3D data, thus allowing to work in the "RGBZ" (color + distance) space.

In this paper, we present a biometric approach based on hand gestures in which the user must "follow" a circle moving on the screen, that acts as a visual stimulus. The circle shifts randomly between pairs of positions – *paths* – within a set of five possible locations; 20 paths are therefore possible. In a preliminary study [3], we considered all 20 paths performed consecutively. The obtained classification results were good for both identification and verification, with success rates above 90%. However, we found that executing all 20 paths was tiring for the user (for example, ATM PINs are usually formed of no more than six digits). Therefore, we decided to carry out a further analysis with the aim to find shorter trajectory lengths that can provide satisfying identification and

* Corresponding author.
E-mail addresses: nahumi@it.upr.ac.id (N. Nugrahaningsih), marco.porta@unipv.it (M. Porta).
Peer review under responsibility of The Korean Institute of Communications and Information Sciences (KICS).

https://doi.org/10.1016/j.icte.2018.04.014

verification rates while allowing a better user experience in real-case applications. In other words, we tried to find a trade-off between the length of the circle's trajectory and the precision of the identification and verification processes. The obtained results are overall satisfactory and indicate that the proposed method can be a viable biometric solution (especially for soft biometric applications, where extremely high identification and verification rates are not required). To our knowledge, the described approach has never been proposed in prior biometric research.

2. Related work

This section provides a brief overview of relevant works exploiting hand gestures for biometric purposes.

A first category of gesture-based biometric applications uses physical devices that need to be kept in the hand or worn. Okumura et al. [4], for example, gathered acceleration data from 22 participants who had to shake an accelerometer. The data were subsequently examined by means of the squared error of Euclidean distance, Error of Angle and DP-matching. Matsuo et al. [5], from the same research team, proposed a template update method to solve the long-term stability problem characterizing their previous study. Zaharis et al. [6] employed seven features from hand-signature gestures acquired with the Nintendo WiiMote device to verify four participants (namely, elapsed time of gesture completion, maximum and minimum acceleration values per axis per time segments, starting and ending sensor positions, and maximum and minimum overall acceleration per axis). Liu et al. [7,8] created a verification system called *uWave*, which included eight predefined gestures previously studied by Nokia [9]. The Dynamic Time Warping (DTW) algorithm was applied on time series data (acquired through Nintendo WiiMote) of each of the three axes. Similarly, Guna et al. [10] exploited Nintendo WiiMote to create an identification system based on three gestures, namely making a signature in the air, picking up the device, and shaking the device. The data obtained from 10 participants were processed through the DTW algorithm.

An unusual gesture detection approach, based on proximity sensing and developed for biometric applications, was created by Reddy and Mashetty [11], who studied the distortion of an electric field produced by hand movements.

Reliable biometric methods exploiting computer vision to recognize gestures are more recent and usually pose less constraints on the user, who does not need to hold any physical device. For example, Kratz and Aumi [12] implemented *AirAuth*, a biometric authentication technique based on in-air hand gestures. The user's fingertip locations and hand center, together with an analysis of the hand movement, were tracked by means of a short-range depth sensor.

In the context of vision-based techniques, Microsoft Kinect was employed in several implementations. For instance, it was used by Tian et al. [13] to develop an authentication system called *Kin-Write*. Eighteen testers performed hand signatures in the air, and features such as hand position and position differences between frames, velocity, acceleration, slope angle, path angle, and log radius of curvature were analyzed using the DTW algorithm. Similarly, Cuevas et al. [14] used the Kinect to distinguish persons through a short sequence of in-air gestures. The system architecture was based on the 'model-view-controller'. Ducray et al. [15] presented a biometric authentication system in which gestures can be changed by the user. Six skeleton points, acquired by means of the Kinect, were analyzed through the DTW algorithm to find the best alignment between gestures. The Kinect was also exploited by Lee et al. [16] for their skeleton and gesture-based user authentication system, which showed that the joint use of skeleton and behavioral data can enhance the precision of user authentication.

Leap Motion is another vision-based sensor that can be used for biometric purposes. For example, Aslan et al. [17] employed this device to explore the potential of mid-air authentication gestures, through many data collected during a three-day science event organized in a shopping mall. Analogously, Chan et al. [18] exploited Leap Motion to perform login and continuous authentication, using both static and dynamic data.

Other techniques (e.g., [19]) are based on measurements of the user's hand pose (i.e., static gestures) in hand sign language. There are also biometric systems not specifically based on hand movements, but which use the Kinect, or similar devices, as a source of data. For instance, Lai et al. [20] focused on the body silhouette, while Wu et al. [21] and Ball et al. [22] exploited the body skeleton. In [23], Wu et al. compared silhouette features to skeletal attributes in terms of authentication performance. The same authors, in [24] proposed a framework to decompose a gesture into three parts, namely initial posture, limb proportions, and gesture dynamics. Lastly, to make up for the limited publicly available databases developed as benchmark data to standardize the research on hand tracking areas, Asaari et al. [25] developed a hand gesture tracking database consisting of 60 video sequences (captured in different situations), which can be also exploited for biometric purposes.

3. Experiment design

3.1. Devices, participants, and experimental procedure

In our studies, hand movements were detected by means of the Microsoft Kinect *v1* sensor, whose RGB camera works at 30 frames per second. Visual stimuli were displayed on a 30-inch (2048 × 1536 pixels) monitor.

For both the first (Section 4) and second (Section 5) studies, we used the same test data obtained from 20 testers (8 males, 12 females), aged between 14 and 50. In the second study, however, we substituted five testers (two males, three females), whose intervals between successive sessions were less than 24 h (unlike the other testers), with five new participants (still two males and three females) whose minimum session distance was 24 h. This way, more reliable results could be obtained. In both cases, since each tester participated in 20 sessions, we obtained a dataset coming from a total of 400 sessions.

In each test session, the tester stood at about 150 cm from the monitor. The Kinect was positioned on top of it, at about 120 cm from the floor (Fig. 1).

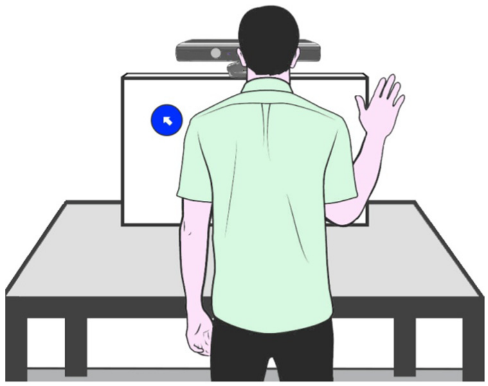

Fig. 1. Experimental setting.

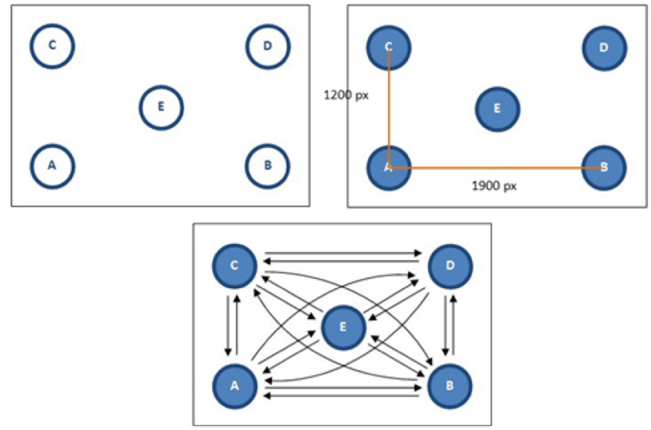

Fig. 2. Circle positions and possible paths.

The visual stimulus was a blue circle appearing (randomly and sequentially) in five predefined positions of a blank white screen — the four corners and the center, as shown in Fig. 2. The tester had to follow the circle with the screen pointer controlled by the hand, keeping it always inside the circle. The 350-pixel diameter circle was displayed in each position for 3.8 s. This time was chosen, after some trials, as a compromise between task duration and significance of the acquired data.

As shown in Fig. 2 (bottom), all 20 paths between all couples of positions were covered by each tester — i.e., the permutation of two circles in five positions. In total, the circle was therefore displayed four times in each location. The trajectory was "continuous", which means that the last position was the starting point for the next destination.

3.2. Acquired data and selected features

The Kinect provided two kinds of raw data: the 2D pointer position on the screen and the hand position in the 3D space. For each sample of each path (1–20) in these raw data, we exploited some features from both data categories.

Given a path AB (where the circle appears first in position A and then in position B), the employed features are the following:

- f1. The average position (in the 2D space) of the screen pointer within the destination circle, i.e. the average x and y coordinates (features *f1a* and *f1b*) of the pointer when it is inside the circle in position B;
- f2. The average position (in the 3D space) of the hand when the screen pointer is within the destination circle, i.e. the average value of the hand's x, y, and z coordinates (features *f2a*, *f2b*, and *f2c*) when the pointer is inside the circle in position B;
- f3. The total time spent by the pointer inside the circle in position B;
- f4. The user's *reaction time*, i.e. the interval between the disappearance of the circle in position A and the instant when the hand starts moving towards the circle in position B;
- f5. The pointer *travel time*, i.e. the interval between the disappearance of the circle from position A and the instant when the pointer enters the circle in the new position B;
- f6. The pointer average speed when traveling from the circle in position A to the circle in position B;
- f7. The hand average speed when the pointer travels from the circle in position A to the circle in position B.

We did not consider two features used in the first study [3], namely the highest and lowest vertical positions reached by the hand, as they are directly connected with physical characteristics of testers (while the other features are related only to the way gestures are performed).

Since each tester performed all possible 20 paths in each session, a row vector of 200 columns (features *f1a*, *f1b*, *f2a*, *f2b*, *f2c*, and *f3* to *f7* for each session) was built. A feature matrix of 400 rows (20 testers × 20 sessions) became the input to the classification process.

4. First study

In a first, preliminary study [3], for the classification process we used only feature vectors obtained from 20 paths. We employed the k-Nearest Neighbors, Naive Bayes, Support Vector Machine, Classification Tree, Neural Network, and Random Forest classifiers. Data division occurred through random sampling (70%:30% and 50%:50%) and 10- and 20-fold cross-validation.

Results were satisfying for both identification and verification. For identification, in the 70%:30% case, we found success rates between 0.73 (Classification Tree) and 0.94 (Support Vector Machines). Verification results were good too, with accuracy values ranging (still with 70%:30% random sampling) from 0.88 (Naïve Bayes) to more 0.99 (the other five classifiers).

The good classification results obtained from this preliminary study suggested that hand gesture driven by a visual stimulus can be exploited for biometric purposes. However, these outcomes were obtained supposing identification and verification processes in which the user performs all the 20 possible paths, which is a rather long and tiring procedure, not suitable for real applications. Therefore, we carried out a further, more in-depth study to find a trade-off between trajectory length and accuracy of the identification and verification processes.

Please cite this article in press as: N. Nugrahaningsih, M. Porta, Soft biometrics through hand gestures driven by visual stimuli, ICT Express (2018), https://doi.org/10.1016/j.icte.2018.04.014.

Table 1
Classification accuracy thresholds.

Trajectory length	CA threshold
1	0.7
2–4	0.8
5–20	0.9

5. Second study

In this second investigation, we aimed to find "optimal" trajectory lengths for both identification and verification, considering all possible continuous trajectories.

Since the visual stimulus is a circle traveling along a trajectory composed of consecutive paths, we considered only the continuous cases within the set of all possible path length combinations C(20,1), C(20,2), . . . , C(20,20). As a result, we obtained 683,052 continuous trajectories, arranged in 20 groups (one for each trajectory length).

To deal with such a high number of cases, we selected the Neural Network classifier. The choice was suggested by a comparison among the six classifiers used in our previous study [3]: Neural Network was, indeed, the only classifier characterized by a good tradeoff between performance and computation time — which is an important factor, due to the very high number of possible continuous trajectories. The employed Neural Network is a multilayer perceptron minimizing an L2-regularized cost function with L-BFGS (normalized data, 10 hidden layer nodes, 1 as a regularization factor and no more than 300 iterations). We used 70% of the dataset for training and 30% for testing.

Both identification and verification were considered, with top-down sub-path selection. First, we processed all the 683,052 continuous sub-paths for the identification case. Then, from the identification results, we selected the combinations whose average Classification Accuracies (CAs) were above certain thresholds (Table 1).

These thresholds were chosen by considering the maximum accuracy and the number of combinations in each group.

When the number of combinations within a group (1–20) was higher than 1000, we chose the 1000 combinations with the highest CA. The selected combinations were then used in the verification process. Since every combination can be permutated in different path arrangements, we think that 1000 is a sufficiently high number to avoid a "learning effect" in testers.

5.1. Identification results

As explained, classification accuracy was calculated for all trajectory lengths, from 1 to 20. Fig. 3 shows that the general trend of the average CA is an increase with the trajectory length (with a couple of small exceptions in correspondence with lengths 12 and 16).

As shown in Table 2, the average CA ranges from 0.747 for the 1-path trajectory to 0.9425 for the 20-path trajectory. Although the classification accuracy may be even acceptable with only one path, a significant improvement can be noticed

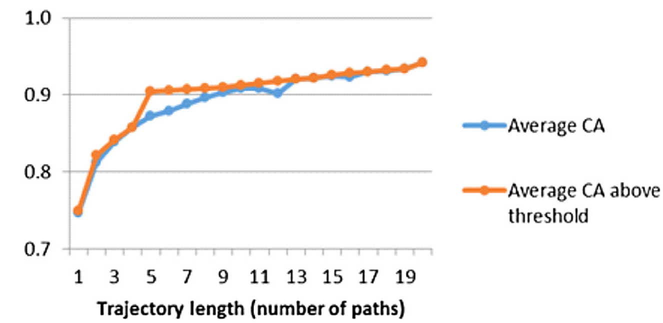

Fig. 3. Identification results: average classification accuracy for the different trajectory lengths.

starting from the 5-path trajectory. We think that an identification procedure with a trajectory composed of five or six paths can be considered a good trade-off between satisfactory "user experience" and acceptable classification accuracy (0.9050 and 0.9053, respectively).

5.2. Verification results

The structure of feature vectors for verification was the same as for identification, but, in this case, the classification process was performed by considering two classes, namely the specific tester and "the others". The procedure was repeated for each tester. Stratified random sampling was applied to select effective samples.

Table 3 shows the verification results for the consecutive paths selected from the identification outcomes (Table 2), according to the defined thresholds (Table 1).

As can be seen, results are very good in terms of Accuracy, Sensitivity, and Area Under Curve (AUC), but less for what concerns Specificity. In the worst case, for the 1-path trajectory, the Specificity is only 0.3191. This means that the system is good for detecting true positive instances, but less in the case of true negative occurrences. However, the plot of results on the ROC plane (Fig. 4) shows that they are all above the random guess line (the straight 45° line): any point below it would mean that the classifier is useless, because it is able to determine whether the claimed identity is true or false in less than 50% of cases.

Given the overall low Specificity, we think that a verification procedure composed of nine paths can be considered a suitable compromise between accuracy and acceptable user experience.

6. Discussion and conclusions

In this paper, we have presented a biometric approach, based on hand gestures, in which a moving circle is used as a visual stimulus.

While considering all 20 possible paths between the five predefined circle positions allows to achieve the best results, performing many gestures in a real identification or verification scenario would be too demanding for a user (in terms of task duration and consequent tiredness). Reducing the number of

Table 2
Identification results.

Traj. length	Number of consecutive paths	Consecutive paths above threshold	Average CA	Average CA above threshold
1	20	19	0.7470	0.7497
2	70	53	0.8120	0.8209
3	260	251	0.8395	0.8412
4	1,035	1,034	0.8581	0.8581
5	3,884	163	0.8718	0.9050
6	11,880	1,128	0.8791	0.9053
7	29,000	6,806	0.8890	0.9067
8	56,590	24,809	0.8968	0.9082
9	91,060	58,617	0.9032	0.9101
10	120,836	97,435	0.9086	0.9124
11	128,839	114,008	0.9087	0.9152
12	108,540	93,745	0.9013	0.9181
13	71,980	71,363	0.9207	0.9209
14	37,560	37,188	0.9215	0.9224
15	15,312	15,263	0.9251	0.9256
16	4,835	4,708	0.9239	0.9280
17	1,140	1,140	0.9296	0.9296
18	190	187	0.9308	0.9322
19	20	20	0.9346	0.9346
20	1	1	0.9425	0.9425

Table 3
Verification results.

Trajectory length	Accuracy	Sensitivity	Specificity	AUC
1	0.9626	0.9965	0.3191	0.9356
2	0.9696	0.9946	0.4943	0.9637
3	0.9724	0.9930	0.5812	0.9704
4	0.9749	0.9933	0.6265	0.9742
5	0.9770	0.9935	0.6648	0.9810
6	0.9781	0.9939	0.6780	0.9818
7	0.9789	0.9942	0.6889	0.9836
8	0.9791	0.9940	0.6962	0.9848
9	0.9799	0.9946	0.7009	0.9858
10	0.9802	0.9947	0.7048	0.9867
11	0.9804	0.9949	0.7065	0.9871
12	0.9804	0.9947	0.7095	0.9878
13	0.9808	0.9951	0.7098	0.9885
14	0.9812	0.9954	0.7124	0.9892
15	0.9818	0.9956	0.7198	0.9897
16	0.9818	0.9957	0.7184	0.9900
17	0.9823	0.9959	0.7226	0.9904
18	0.9825	0.9960	0.7254	0.9909
19	0.9826	0.9961	0.7273	0.9916
20	0.9828	0.9963	0.7264	0.9920

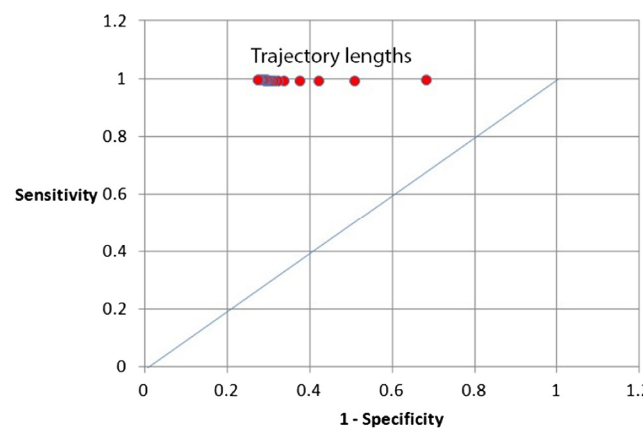

Fig. 4. ROC plane for verification.

positions in which the circle appears decreases the user's effort, making the proposed approach a much more viable solution.

Hand gestures are usually intuitive and easy to perform. Of course, the biometric technique we propose falls in the so-called "soft biometrics" category, as it can only provide a probability that specific features are associated to a certain person rather than finding a one-to-one matching between certain characteristics and a subject. For identification purposes, this means that the method can be only employed when 100% precision is not necessary. For verification aims, however, the approach can be used in addition to traditional authentication techniques, as a further confirmation of the user's claimed identity. Moreover, gesture-based biometrics can be very useful in those cases in which touchless procedures are mandatory (e.g., when the identity check must occur at a distance, such as in sterilized environments or semiconductor factories, as explained in [17]).

Overall, the achieved results are in line with those provided by the vision-based techniques presented in Section 2 [12–18]. What is different, however, is the way hand gestures are performed. Unlike "unconstrained" hand movements (such as writing a signature in the air), in the proposed approach the user's task is very simple, and simple is also the visual cue that guides it: a moving circle displayed on the screen. In our experiments, all testers achieved this goal correctly since the very beginning of the first test sessions.

Regarding identification, we have obtained an average classification accuracy ranging from 0.747 (one path) to 0.9425 (20 paths). Of course, the longer the trajectory the higher the accuracy, since more data are involved in the recognition process. However, a major improvement can be observed starting from the 5-path trajectory (0.905). This suggests that five paths are enough to carry out reasonably reliable identification procedures, with more than 90% of correct recognitions.

Accuracy is fairly good for verification too, always greater than 0.962. Sensitivity is very good as well, higher than 0.99 even for 1-path trajectories — i.e., the genuinely claimed identity is correctly recognized in more than 99% of cases. On the other hand, specificity is moderately low (although results on the ROC plane are all above the random guess line). A 9-path trajectory (less than half of the full trajectory length) is however enough to achieve a specificity value of 0.7009 — i.e., a falsely claimed identity is detected in 70% of cases. Even if this is not adequate for high-security applications, it may be acceptable in soft biometric scenarios or when multibiometric systems are employed. Compared to the first study [3], the reduction in specificity that can be observed for length 20 is due to the five different testers introduced and (especially) to the exclusion, as features, of the highest and lowest vertical positions reached by the hand.

Future work will study the integration of the proposed method with other solutions, such as facial recognition (e.g. [26]) or general body movements, to implement multimodal biometric systems. Moreover, to increase the precision of gesture detection, the joint use of two Kinect devices, in parallel, will be considered.

While several biometric systems have been developed to date which exploit data coming from hand movement, none of them uses a visual stimulus as a guiding cue. To the best of our knowledge, a biometric approach based on hand gestures driven by visual stimuli has never been proposed in prior biometric research. We therefore think that this work can be a starting point for deeper and more focused investigations, stimulating further studies on the subject.

Conflict of interest

The authors declare that there is no conflict of interest in this paper.

References

[1] Z. Zhang, Microsoft kinect sensor and its effect, IEEE MultiMedia 19 (2013) 4–10.

[2] J. Guna, G. Jakus, M. Pogačnik, S. Tomažič, J. Sodnik, An analysis of the precision and reliability of the leap motion sensor and its suitability for static and dynamic tracking, Sensors 14 (2014) 3702–3720.

[3] N. Nugrahaningsih, M. Porta, G. Scarpello, A hand gesture approach to biometrics, in: Proc. ICIAP 2015 Workshops, Springer International Publishing, 2015, pp. 51–58.

[4] F. Okumura, A. Kubota, Y. Hatori, K. Matsuo, M. Hashimoto, A. Koike, A study on biometric authentication based on arm sweep action with acceleration sensor, in: Proc. 2006 International Symposium on Intelligent Signal Processing and Communications (ISPACS '06), Springer International Publishing, 2006, pp. 219–222.

[5] K. Matsuo, F. Okumura, M. Hashimoto, S. Sakazawa, Y. Hatori, Arm swing identification method with template update for long term stability, in: Proc. 2007 International Conference on Biometrics, (ICB '07), Springer Berlin Heidelberg, 2007, pp. 211–221.

[6] A. Zaharis, A. Martini, P. Kikiras, G. Stamoulis, User authentication method and implementation using a three-axis accelerometer, in: Proc. 2nd International ICST Conference (MOBILIGHT '10), 2010, pp. 192–202.

[7] J. Liu, Z. Wang, L. Zhong, J. Wickramasuriya, V. Vasudevan, uWave: Accelerometer-based personalized gesture recognition and its applications, in: Proc. IEEE International Conference on Pervasive Computing and Communications (PerCom '09), 2009, pp. 1-9.

[8] J. Liu, L. Zhong, J. Wickramasuriya, V. Vasudevan, User evaluation of lightweight user authentication with a single tri-axis accelerometer, in: Proc. 11th International Conference on Human-Computer Interaction with Mobile Devices and Services, 2009, p. 15.

[9] J. Kela, P. Korpipää, J. Mäntyjärvi, S. Kallio, G. Savino, L. Jozzo, S.D. Marca, Accelerometer-based gesture control for a design environment, Pers. Ubiquit. Comput. 10 (2005) 285–299.

[10] J. Guna, I. Humar, M. Pogacnik, Intuitive gesture based user identification system, in: Proc. 2012 35th International Conference on Telecommunications and Signal Processing (TSP '12), pp. 629-633.

[11] M.S.S. Reddy, M.G.K. Mashetty, Implementation of free-air hand motion signatures based control for home entertainment, Int. J. Curr. Eng. Technol. 5 (4) (2015) 2862–2867.

[12] S. Kratz, M.T.I. Aumi, AirAuth: a biometric authentication system using in-air hand gestures, in: Proc. 2014 Conference on Human Factors in Computing Systems (CHI '14), Extended Abstracts, 2014, pp. 499-502.

[13] J. Tian, C. Qu, W. Xu, S. Wang, KinWrite: Handwriting-based authentication using kinect, in: Proc. 20th Annual Network & Distributed System Security Symposium (NDSS '13), 2013.

[14] H. Cuevas, A.M. Bernardos, X. Wang, L. Bergesio, J.R. Casar, Integrating gesture-based identification in context-aware applications: a system approach, in: Proc. 2014 10th IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob '14), 2014, pp. 257-264.

[15] B. Ducray, S. Cobourne, K. Mayes, K. Markantonakis, Authentication based on a changeable biometric using gesture recognition with the KinectTM, in: Proc. 2015 International Conference on Biometrics (ICB '15), 2015, pp. 38-45.

[16] H.F. Lee, Y.S. Lu, J.L. Huang, C.L. Hu, A skeleton and gesture based user authentication system, in: Proc. 2015 8th International Conference on Ubi-Media Computing (UMEDIA '15), 2015, pp. 254-258.

[17] I. Aslan, A. Uhl, A. Meschtscherjakov, M. Tscheligi, Mid-air authentication gestures: an exploration of authentication based on palm and finger motions, in: Proc. 16th International Conference on Multimodal Interaction (ICMI '14), 2014, pp. 311-318.

[18] A. Chan, T. Halevi, N. Memon, Leap motion controller for authentication via hand geometry and gestures, in: Proc. HCI International '15, 2015, pp. 13-22.

[19] S. Fong, Y. Zhuang, I. Fister, I. Fister Jr., A biometric authentication model using hand gesture images, BioMed. Eng. OnLine 12 (2013) 111.

[20] K. Lai, J. Konrad, P. Ishwar, Towards Gesture-based user authentication, in: Proc. 9th IEEE International Conference on Advanced Video and Signal-Based Surveillance (AVSS '12), 2012, pp. 282-287.

[21] J. Wu, J. Konrad, P. Ishwar, Dynamic time warping for gesture-based user identification and authentication with Kinect, in: Proc. 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP '13), 2013, pp. 2371-2375.

[22] A. Ball, D. Rye, F. Ramos, M. Velonaki, Unsupervised clustering of people from 'skeleton' data, in: Proc. 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI '12), 2012, pp. 225-22.

[23] J. Wu, P. Ishwar, J. Konrad, Silhouettes versus skeletons in gesture-based authentication with Kinect, in: Proc. 11th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS '14), 2014, pp. 99-106.

[24] J. Wu, P. Ishwar, J. Konrad, The value of posture, build and dynamics in gesture-based user authentication, in: Proc. 2014 IEEE International Joint Conference on Biometrics (IJCB '14), 2014, pp. 1-8.

[25] M.S.M. Asaari, B.A. Rosdi, S.A. Suandi, Intelligent biometric group hand tracking (IBGHT) database for visual hand tracking research and development, Multimed. Tools Appl. 70 (2012) 1869–1898.

[26] F. Battaglia, G. Iannizzotto, L. Lo Bello, A person authentication system based on RFID tags and a cascade of face recognition algorithms, IEEE Trans. Circuits Syst. Video Technol. 27 (8) (2017) 1676–1690.

Please cite this article in press as: N. Nugrahaningsih, M. Porta, Soft biometrics through hand gestures driven by visual stimuli, ICT Express (2018), https://doi.org/10.1016/j.icte.2018.04.014.