Biometric Verification Based on Hand Thermal Images

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Abstract

The paper presents a biometric recognition methodology based on hand thermal information. We start with a hardware presentation, specially designed for this research in a form of thermal sensor plate delivering hand thermal maps, which is a significantly cheaper alternative to thermal cameras. We use a heuristic feature selection technique employing mutual information (mRMR) and well known space transformation methods (PCA and its combination with the LDA) to develop optimal biometric features by selecting those parts of the hand, which deliver the most discriminating personal information. Two different classifiers (k-NN and SVM) are applied and evaluated with a database of hand thermal maps captured for 50 different individuals in three sessions: two at the same day (enrollment attempts), and the third captured a week apart (verification attempt). We achieved 6.67% of an average equal error rate (EER), what suggests that temperature distribution of an inner part of human hand is individual. This may serve as e.g. *supporting modality of two-modal biometric recognition (merged with hand geometry or palm print techniques), or may be a good candidate for hand liveness detection approach, as hand thermal maps are difficult to be copied and reconstructed on an artificial object imitating a human hand. To our best knowledge, this is the first work presenting the use of a human hand thermal maps as a direct source of biometric features.*

1. Introduction

Thermal imaging is not so common as the usage of visible light when capturing physical biometric characteristics. This is caused by a few factors, and the most significant reason still concerns the cost of thermal cameras, being often out of proportion to the obtained biometric recognition accuracy. However, assuming for a while that the hardware cost plays a supporting role (or expecting its fast and serious decrease), and thus having no bias related to the expenses, we may spot more gladly at least three areas of thermal imaging application in biometrics. Firstly, thermal images may deliver a larger discrepancy between the object of interest and the background. Hence, it is often combined with standard biometric methods to optimize the data segmentation. Secondly, the distribution (typically uneven) of our body temperature is relatively difficult to be copied and reconstructed on artificial objects imitating authentic biometric characteristics. This allows to enhance the biometric modalities with liveness testing, which matches the observed temperature distribution with common (or subject-related) model of body thermal characteristics. Last but not least, we may use the thermal information as a source of biometric features. On the one hand, our average body temperature may significantly vary due to illness or easiness of heat exchange between our tissues and an outside environment. On the other hand, the thermal map of our skin is a consequence of metabolism of tissue cells, individual anatomy related to the heat accumulation, and – to some extent – muscle work. Neglecting the latter (we assume in this work static measurement, not directly preceded by extensive muscle exercises), the former factors should lead to individual features, corresponding with the uniqueness of a given body part physiology.

All the above three areas of thermal imaging application are attractive for biometrics, yet the last one, related to the recognition of the individual through his or her thermal unique features seems to remain an emerging technology. We have developed a complete biometric recognition methodology employing local temperature information of an inner part of the hand. This paper presents our hardware setup, feature selection and classification methodologies, and the results that partially satisfy a general curiosity related to the usefulness of the hand thermal maps in biometrics. The proposed method should not be confused with hand geometry biometrics that employs hand silhouette, or with palm biometrics, which does not use the temperature information. Thermal biometrics is also significantly different from hand vein recognition, as in the latter approach the vein patterns are captured by using the effect of higher infrared light absorption by the hemoglobin when compared to the absorption of neighboring tissues. We thus intentionally do not compare performance results for hand thermal biometrics with palm or vein recognition, as they all represent heterogeneous and distant modalities.

2. Related work

Most of the scientific literature devoted to thermal imaging in biometrics focuses on human face, and is much less populated by works employing information about the temperature of a hand. Typically hand thermal imaging plays a supporting role in segmentation process in hand geometry or vein recognition. Wang *et al*. [4] uses thermal imaging instead of near infrared light to extract the palm vein patterns, which are then skeletonized and matched with the use of Hausdorff distance. Similar approach is proposed by Kumar *et al*. [1], yet these authors define the features as branch points of the vein skeleton lines, or calculate skeleton line orientations and locations within local image boxes. The authors report 3.5% of the false rejection rate at the false acceptance rate set to 0.01%, obtained for a database of images collected for 100 individuals. Mekyska *et al*. [2] propose a few methods of hand thermal image segmentation, and promote the image registration technique as the most accurate among others, based on *e.g*. active shapes or Fisher information. Finally, Wang *et al*. [5] proposes a recognition method based on geometrical features of the hand silhouette derived from the hand thermal images. The authors tested their approach with the database gathering samples for 30 subjects, and report 99% of the correct recognition rate for nonlinear classification (realized through a neural network).

Despite our best efforts and sincere will to compare our proposal with similar solutions, we did not find any earlier work describing extraction and matching of biometric features based directly on distribution of a hand temperature.

3. Database of thermal hand images

3.1. Hardware characteristics

We use a plate of temperature sensors as an alternative to the thermal imaging by a camera, Fig. 1. The upper side of the plate consists of 1012 thermal sensors arranged in 23 columns and 44 rows separated by 5 mm distance. Every second row is shifted by half of the distance between columns, as such arrangement of sensors minimally interferes with a typically vertical alignment of fingers during the capture. We may thus say that the capture process results in a specific "thermal image" (or "map") of a hand, and its resolution is 23×44 "pixels".

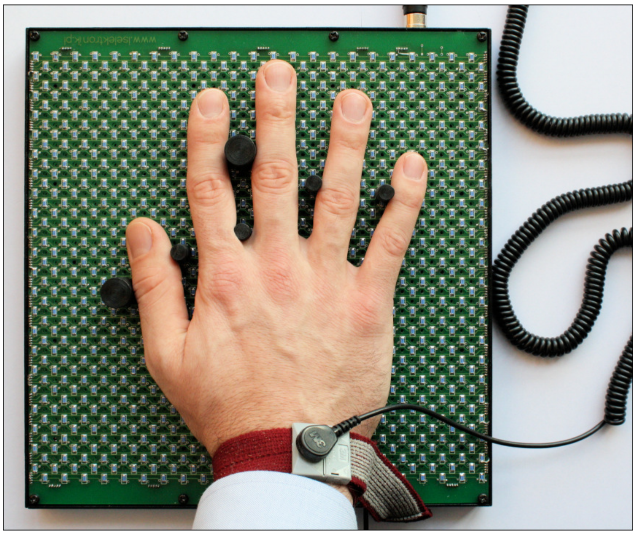

Figure 1. Top view of the sensor plate used in this work. Six pegs (fixed during all experiments) help subjects in correct positioning of their hand.

Each sensor measures temperature within a range of 0-60°C with an accuracy of 0.1/0.3°C (relative/absolute). All the sensors are of the same type and have been carefully chosen from a large set of sensor units before final soldering them into an electronic circuit. We believe that this care is not an exaggeration as this increases a homogeneity of electronic elements, and thus the reliability of the device.

To capture a thermal image with an adequate accuracy, the hand skin should have physical contact with the sensors, yet the hand pressure information (possibly helpful since the temperature may depend on the object's pressure in contact measurement) cannot be assessed due to lack of the pressure sensors in the device. For a better stability of the thermal pattern mapping, the plate has threaded holes between each sensors pair to allow for any installation of the positioning pegs. The pegs' positions are fixed when building a measurement station, and not changed throughout the device lifespan. Additionally, due to high risk of the electrostatic discharge, the device is equipped with a grounding cable connected with a hand through wristband with a metal connector (visible in Fig. 1 on the right). Sensor outputs are read sequentially. We need 4 ms to read a single sensor value, and approximately 4.5 seconds are required to construct the entire thermal map (including communication burden between the device and the host).

3.2. Database collection

The database employed in this research is a part of a larger *BioBase* multimodal set, collected by our team. As the database is legally registered, the written consent was signed by each volunteer prior to the measurement. The graphical and verbal instructions (especially related to hand positioning) had been given to each subject to guarantee a correct triggering of the measurement process and to minimize failures to acquire. The quality of each resulting sequence was assessed on-line by an operator, and a few incorrect measurements were repeated.

The entire data collection lasted five months (from summer to early winter), what positively influenced a diversification of outside conditions during capture. We have collected the thermal maps for 50 different subjects (35 men and 15 women) in an office environment and in three different sessions: two first organized at the same day, yet separated by a few hours, and the third carried out approximately a week after the second one. Each session yielded a single sequence of 24 thermal maps per hand (obtained in one presentation, without changing the hand position): the first map was captured after 4.5 seconds, and the last one after 108 seconds, Fig. 2.

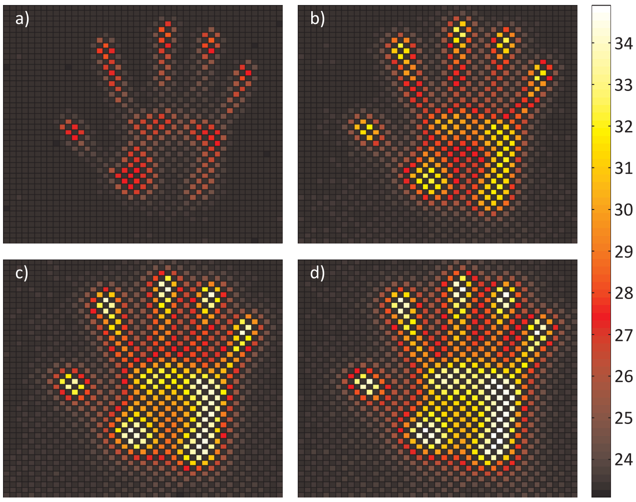

Figure 2. Example thermal images captured after a) 4.5, b) 32, c) 72 and d) 108 seconds after the first contact of the hand with the sensor plate (*i.e.* four selected images from a complete sequence of 24 maps). We may observe gradual increase of the sensors temperature, as well as the influence of the hand on the neighboring sensors having no direct contact with the skin. Color bar on the right is calibrated in Celsius degrees.

Collecting sequences rather than single maps allows for investigation of the optimal heating time, being an additional degree of freedom when optimizing the system setup. Each session data is accompanied by basic personal data, as well as background temperature and humidity. The device was calibrated prior to each presentation. Calibration is realized by the device driver, and during this process one should first stabilize the temperature of the sensors leaving the device for a couple of minutes intact. Then deviations of the sensors temperature from the global average can be automatically stored in the driver's memory.

4. Building a hand thermal biometrics

4.1. Estimation principles

To build a biometric recognition system based on hand thermal images we need to estimate a) the best (usable) thermal sensors, or an optimal transformation of the feature space highlighting individual properties of a hand, b) classifier parameters and the corresponding acceptance thresholds, and c) the required measurement time (as the thermal plate warms up slowly). In the first estimation task (a) we do not use fixed region of interest, as the mRMR method selects the optimal features by itself, and the PCA-based transformation employs the entire set of thermal sensors. In task related to classifier choice (b) we check the usefulness of simple linear classifiers (due to generalization capabilities). Optimal measurement time (task c) is assessed by analyzing all 24 thermal maps acquired in each session, and the winning map points out the required presentation time.

In all these tasks, a use of collected dataset cannot be accidental, and must coincide with an expected application of the method. Typical biometric enrollment process requires multiple presentations, often complemented within a single session, while the verification attempts are realized some time apart. We thus follow this typical scenario and use two first samples (collected at the same day) as the enrollment data, while the third one (collected a week apart) serves as a verification probe. The classifiers used in this work are trained solely with the enrollment samples, and tested with the remaining verification sample, *unknown* to the classifier when being trained. This approach will deliver significantly higher error rates when compared to the evaluation based on the same session samples, yet will better reflect the system's accuracy expected to be achieved in operational scenarios.

The next subsections summarize all the above aspects of the proposed method development.

4.2. Feature selection methods

Minimum Redundancy, Maximum Relevance (mRMR). Peng *et al*. [3] propose to use a mutual information to select best features employed in classification problems. This approach employs Kullback-Leibler divergence of a product $P(X)P(Y)$ of two marginal probability distributions $P(X)$ and $P(Y)$ from the joint probability distribution $P(X,Y)$. The selection criterion is thus based on the maximum statistical dependency between the variables X and Y, yet the direct implementation of the maximum dependency condition is difficult. Peng *et al.* developed an equivalent form of this criterion called the *minimal-redundancy maximum-relevance* (mRMR) being a heuristic approach which selects those features that increase the mutual information, then excludes "redundant" ones. Each thermal sensor is equated with as a single feature (*i.e*. the entire set of features includes 1012 elements), and a separate recognition method – employing different numbers of the first (*i.e.* the best) features sorted by mRMR – is built and analyzed in terms of the EER (equal error rate[1]). Minimum value of EER suggests the optimal set of features and the best measurement time (for an applied classification method).

Approaches assessing the usefulness of single features, as mRMR, additionally point out the best thermal sensors (*i.e.* their number and location), which closely correspond to the areas of a hand delivering optimal biometric thermal features (Fig. 3). This serves as a hint how to reduce the number of sensors in such devices (decreasing a hardware cost) and prevents us from applying fixed and arbitrary (*e.g.* rectangular) region of interest.

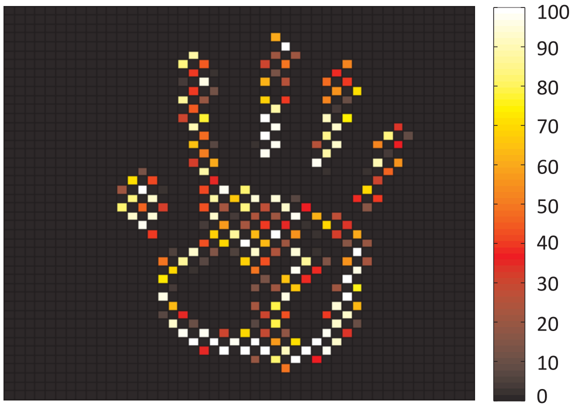

Figure 3. The graph shows how frequently, and which thermal sensors are selected after 255 iterations of the mRMR method, assuming we look for 120 best features. The colorbar on the right is scaled in percents, *i.e.* the lighter color refers to a higher willingness of the mRMR to select a given sensor. Note that feature selection mechanism correctly selects sensors having contact with a hand, and rejects all the background sensors.

Principal Component Analysis (PCA) and its combination with Linear Discriminant Analysis (PCA+LDA). PCA (also known as Karhunen-Loeve's transform) and LDA (closely related to Fisher's linear analysis) are widely documented in the scientific literature, and successfully used for reduction of feature space dimensionality. PCA finds a subspace $\mathcal{S}^M$ of the input space $\mathcal{V}^N$ of – possibly correlated – variables (where $M \leq N$) and the basis vectors of $\mathcal{S}^M$ correspond to the maximum variance of variables in the original space $\mathcal{V}^N$. As typically $M \ll N$, the PCA offers a significant reduction of space dimensionality, particularly important for spaces sparsely populated by variable exemplars, what have a positive impact on further classification reliability. In this paper we calculate the EER for each number of the first n principal components, where $n = 1, ..., N$, and $N = 1012$ corresponds to the number of thermal sensors (as we employ the entire set of thermal sensors in PCA), and select the solution (i.e. the number of first principal components) with the lowest error rate.

[1] we use zero-order approximations of false match and false non-match error functions to calculate the equal error rate

LDA considers (in addition to the PCA) a within-class variability, and employs it along with between-class variance to find a linear combination of input variables building an optimal hyperplane that separates input samples given their class affiliations. However, a small number of within-class probes (*i.e.* two enrollment samples in a database used in this work) may result in singular within-class scatter matrices, making the LDA infeasible. Fortunately, this singularity may be avoided by applying the PCA prior to the LDA. This combination is often referred to as PCA+LDA, and typically outperforms PCA or LDA applied separately [6]. In PCA+LDA feature estimation approach we still find the optimal number of principal components in a first step (PCA), and the LDA is always applied after the PCA transformation. Similarly to the previous approaches, we choose configuration offering the lowest EER.

4.3. Classification methods

Limited number of training samples for each class (*i.e.* two enrollment samples per hand) calls for classification techniques with strong generalization capabilities. We thus engage two linear classifiers (k-nearest neighbors and support vector machine with linear kernel) and skip showing results for nonlinear neural network, as the experiments revealed a high tendency to network overtraining in this task, poor generalization and hence higher error rates.

k-Nearest Neighbors (kNN) method classifies incoming (unknown) points by a majority voting realized by k nearest neighboring elements to the incomer, given a distance metric. In this work we realize a binary classification task, *i.e.* the verification sample is classified to the claimed identity class, or the claimed identity is rejected. We set $k = 1$ and use both the enrollment samples in voting. The Euclidean distance is used, the maximum allowed distance between new and the existing samples is set at the enrollment (training) stage, and serves at the verification as the acceptance threshold.

Support Vector Machine (SVM) is a supervised learning technique that finds a hyperplane maximizing a gap between training samples representing different classes. Simple "kernel trick" allows to solve nonlinear classification problems, yet we stay with a linear classifier. We build a separate SVM for each subject based on two enrollment samples so that to classify subjects' new probes against impostor exemplars. Each SVM is thus tested for the remaining (third), verification thermal map (unknown at the training stage).

4.4. Estimation results

Biometric recognition scenario, as detailed in 4.1, is applied for any possible measurement time and any possible transformation of the feature set. We may say that each such configuration constitutes an independent biometric recognition system, and thus its reliability may be assessed by calculating the EER. We repeat a system building scenario 100 times, each time employing a data corresponding to 25 subjects chosen randomly from a full set of 50 volunteers. Hence, an optimal configuration (number of features / capture time) is based on average (not single) EER.

Above analysis is repeated independently for a few combinations of feature selection and classification methods. We calculate an average EER as a two-argument function of capture time and number of features (when mRMR is applied) or number of principal components (for PCA and PCA+LDA approaches). Figures 4 and 5 present results obtained when the mRMR is applied for feature selection, and the class membership of the enrollment samples are estimated by kNN and SVM classifiers, respectively. Optimal combinations of capture time and number of features (minimizing EER) yield in both cases substantial reduction of the feature space (139 and 50 thermal sensors for kNN and SVM classifiers are used, respectively).

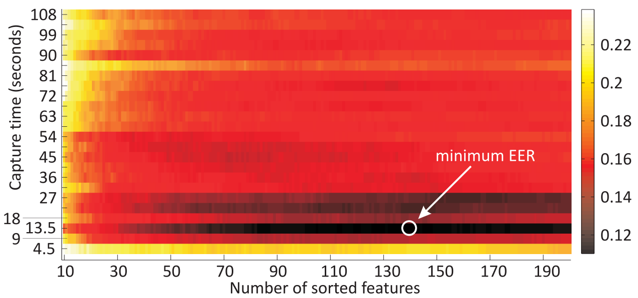

Figure 4. Equal error rate for different combinations of the measurement time (multiple of 4.5 seconds) and number of best features (sensors). The mRMR feature selection and kNN classification methods are used. Minimum of average EER=11.03% is achieved for 139 best features (*i.e.* sensors) and 13.5 second measurement time.

Since kNN classifier leads to lower EER when compared to the SVM, we further narrow analysis of PCA and PCA+LDA feature space transformation methods to this classification approach, Fig. 6 and 7. Again, significant reduction of the feature space may be observed, similarly to the mRMR feature selection method. PCA suggests using 115 principal components, and adding the LDA analysis limits the feature space to only 25 dimensions. The latter estimation approach additionally yields the best system performance, *i.e.* EER$\in \langle 0.027, 0.116 \rangle$, with its sample mean value equal to 0.067.

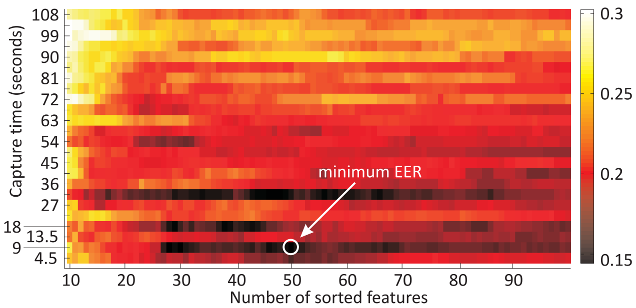

Figure 5. Same as in Fig. 4 except that SVM classifier is used. Minimum of average EER=14.43% is achieved after 9 seconds and only 50 features are used in thermal maps.

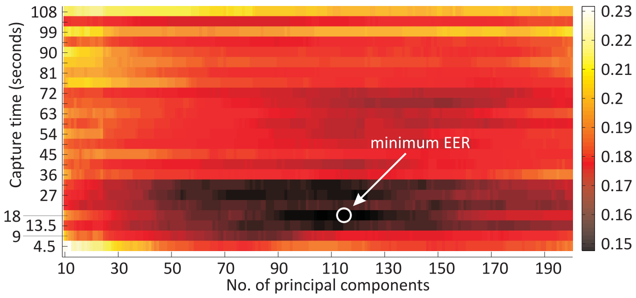

Figure 6. Equal error rate for different combinations of the measurement time and number of principal components returned by PCA. k-NN classification method is applied in a new 115-dimensional feature space (*i.e.* 115 principal components are used), and minimum EER=14.76% is achieved after 18 seconds of the measurement.

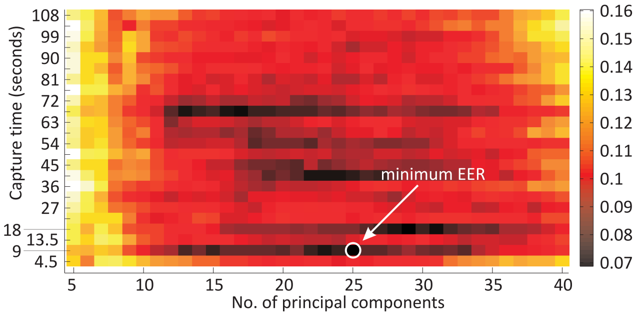

Figure 7. Same as in Fig. 6, except that the LDA is performed after the PCA. Minimum EER=6.67% is achieved after 9 seconds and only 25 principal components are used.

Additionally to the reduction of feature space dimensionality, all estimation techniques selected shorter capture times (remind that the measurement time is a multiple of 4.5 seconds due to hardware capabilities). This may contradict our intuition prompting that the longer measurement times should more accurately reflect real hand temperature distributions, and thus result in more reliable recognition. However, such reasoning neglects a thermal conduction phenomenon, what makes any single sensor accumulating the heat associated to a larger skin area once the measurement time increases. This smooths away thermal maps (as can be spotted in Fig. 2) and subtle individual thermal features of a skin become hidden in prevailing average (cumulated) temperatures.

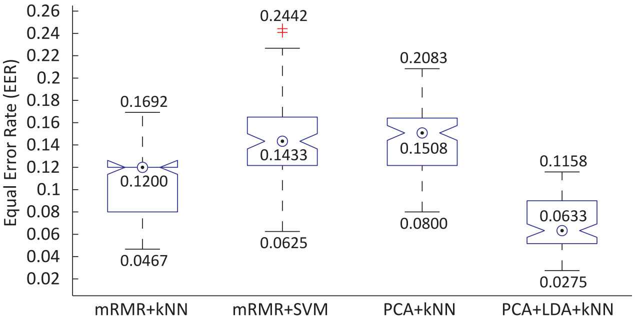

Figure 8. Boxplots for all four variants of feature space transformation and classifier. Central dots represent median EER, edges of the boxes correspond to 25th and 75th percentiles of the EER distribution and whiskers cover 1.5 of the interquartile range. Maximum and minimum values are also depicted above and below the whiskers, respectively.

Figure 8 summarizes the recognition accuracy obtained for different feature selection and classification approaches. Median EER (as a complement to average presented earlier) as well as its minimum and maximum values are provided. We may finally select the PCA+LDA feature space transformation method and the kNN classification as the winning approach to recognize the hand thermal maps.

5. Conclusions

Results presented in this paper suggest that we can claim individuality of hand skin temperature distributions. However, we should interpret these results cautiously. Firstly, reduced dimensions of the feature space (applied in classification) were smaller than the number of classes. This easily (and not surprisingly) has lead us to perfect classification (*i.e.* EER=0) when only the enrollment samples were used (due to possibility of performing a linear classification of any N points scattered within N-dimensional space). This however raises a question if the classifiers had a chance to locate the classification hyperplanes adequately to the problem being solved. Observing nonzero error rate when using verification samples (as depicted in Sec. 4.4) may call for collecting definitely larger datasets to populate the feature space less sparsely, and additionally reflects limited stationarity of hand thermal maps. Secondly, the way of measurement (thermal sensors plate) cannot be neglected as the measurement repeatability and ergonomics may be seriously increased by using thermal cameras (yet accepting a higher cost of the sensor).

Limited accuracy of this method should not however disqualify its usage in biometrics. Thermal maps deliver information that cannot be obtained when the hand is measured in a visible or near-infrared light. Hence a two-modal system can be build combining geometry and thermal features, that can be measured at the very same presentation. Additionally, hand temperature is relatively difficult to be measured without the will of the subject, and its accurate reconstruction (*e.g.* in a hand imitation, or cadaver part) is almost impossible. This perfectly matches recent endeavors to equip biometric systems with liveness detection techniques. Expanding existing hand geometry sensors (relatively easily to be deceived, if only a hand silhouette is measured) with hand thermal sensors may thus significantly increase their security as the presentation attack would be far more difficult to be succeeded.

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