The start of an ear identification system

Assignment #1

Image Based Biometrics 2018/19, Faculty of Computer and Information Science, University of Ljubljana

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***Abstract*—In this paper we give insights in the starting steps of creating an ear based biometric identification system. Additional we present an upgrade to the AWE Toolbox [1]. This we achieve by extending the database and improve on the accuracy of the feature extractors.**

I. Introduction

In moder society data protection is of at most impotence. We want only authorized people to have access to their data. Basic systems use some kind of memorizable secret key (password, PIN, ...) for that. The problem of those systems is that the secret key can be stolen. So the solution of advanced systems is to use something that is hared or impossible to steal. They use biometrics, features that are bound by biology and are thereby hared to forge. In this paper we propose some staring steps of creating such a system based on peoples ears. We base our system on the AWE Toolbox [1]. We extend the database and improve the feature extracting.

II. Methodology

A. Image acquisition

First step in creating a biometric system is data acquisition. This is impotent because we want test our system and validate its functionality. By data we actually mean photos of peoples ears. Such a database of photos is already included in the AWE Toolbox. We extend it by providing 20 additional subjects, 30 pictures each. As the process of manually downloading, cropping and annotating pictures from the internet is wary tedious we created a simple gui program (Figure 1) to speed up the process. The program is publicly available from https://github.com/robertcv/image_acquisition.

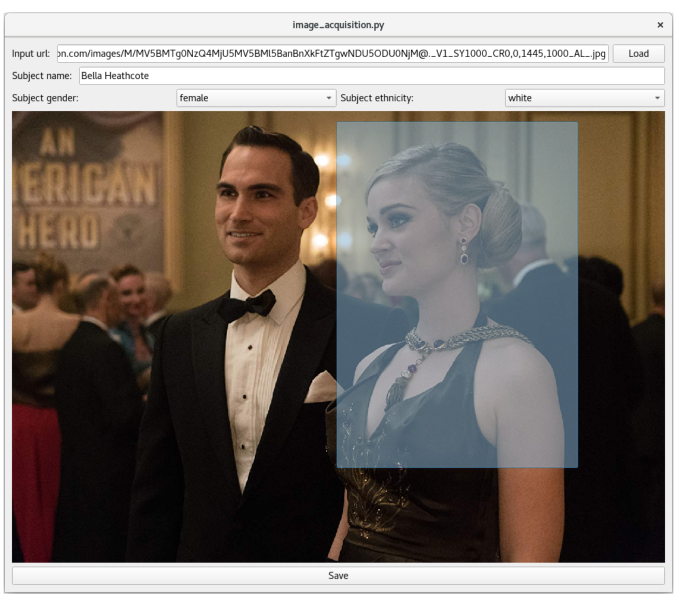

Figure 1. Graphical user interface of the Image acquisition program.

B. Feature extraction

Next step in the biometric pipeline is to extract properties from pictures of ears that are invariant to the envelopment in which the picture ware taken. This is especially impotent because we want to build a robust system. Many so called feature extractors are available in the AWE Toolbox. We make improvements to Rotation invariant local phase quantization [2] and add a newly developed one called Robi extractor.

1) Rotation invariant local phase quantization: RILPQ (Rotation invariant local phase quantization) presents an extension to LPQ(Local phase quantization). This is based on encoding local image texture in Fourier phase spectrum using binary strings. RILPQ extends that by first rotating the local neighborhood with accordance to its characteristic orientation.

2) Robi extractor: The main idea of our feater extractor is to fined the direction of edges in the picture and thereby encode the shape of the ear. This was achieved by first downsizing the images and then convolution with the flowing three filters:

$$a = \begin{bmatrix} 1 \\ -1 \end{bmatrix}, b = \begin{bmatrix} 1 & -1 \end{bmatrix}, c = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

Each of the three output images were then flattened and combined into one feature vector.

III. Results

We found that for the RILPQ the default parameters are not the optimal one. Through testing (Figure 2) we discovered that for this particular dataset the best parameters are $w = 9$ (local window size) and $a = 4$ (number of angels).

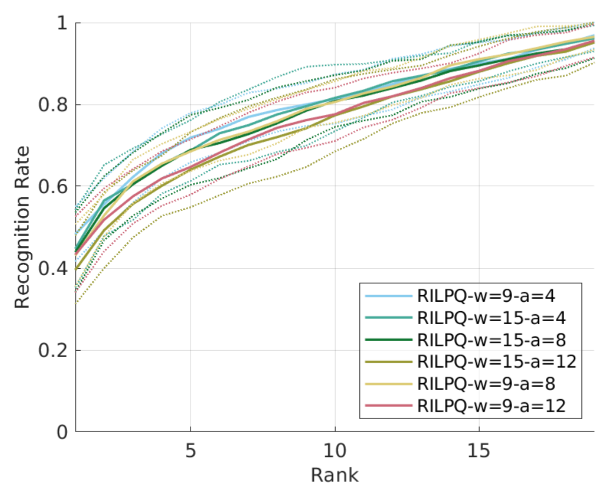

Figure 2. CMC curve for RILPQ with different parameters.

We also tested the performance of the newly developed Robi extractor. On Figure 3 we observe that it's not far from the aforementioned RILPQ. During our testing we also saw a 2x speedup compared to RILPQ and we can thereby justify the performance impact.

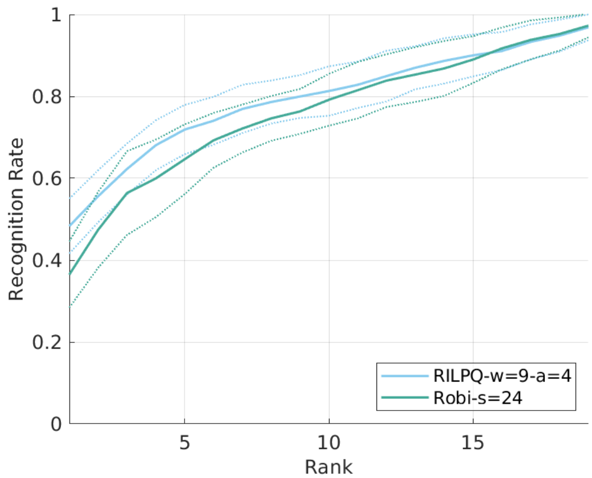

Figure 3. Comparison between the RILPQ and Robi extractor CMC curve.

IV. Conclusion

We successfully extended the AWE Toolbox and presented the two starting steps of creating an ear identification system. In the next steps we suggest to look at the finale part of the biometric pipeline which is matching.

References

[1] Z. Emersic, V. Struc, and P. Peer, "Ear Recognition: More Than a Survey," *Neurocomputing*, 2017.

[2] V. Ojansivu, E. Rahtu, and J. Heikkila, "Rotation invariant local phase quantization for blur insensitive texture analysis," in *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on.* IEEE, 2008, pp. 1–4.