CHALLENGING EYE SEGMENTATION USING TRIPLET MARKOV SPATIAL MODELS

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ABSTRACT

We present a novel implementation of Triplet Markov Fields (TMF) for the unsupervised region segmentation of challenging eye images, representative of the iris recognition context. Results confirm the interest of such models over the classical Hidden Markov Field (HMF) and traditional gradient-based approaches for iris and periocular detection. We show that the precision of the resulting normalization circles is largely improved through the use of such TMF model as well as the quality of the image segmentation, despite of various degradations. These results are promising for further integration of TMF approaches in iris verification systems.

Index Terms— Iris, Biometry, Markov Model, Triplet Markov Fields, Segmentation.

1. INTRODUCTION

Among the various physiological biometric characteristics, which may help personal identification, iris pattern has attracted great attention these last decades. This is mainly due to its distinctive features and high reliability for personal identification, which has been assessed in a variety of situations [1], [2], [3]. However, this high level of performance can only be obtained at the price of heavy constraints imposed to the person. Recent trends tend to loosen these constraints in order to make the systems more user friendly, but the resulting image quality is therefore severely degraded due to blur or illumination variability. When the iris texture is highly degraded, using periocular information in complement of the classical iris texture has been shown to bring important improvements [4]. Periocular information corresponds to the shape of the corner of the eyes or the eyelashes and is in general, difficult to detect with gradient-based algorithms.

Building an iris recognition system requires isolating the iris texture from other elements of the image such as eyelids, shadows or glasses as accurately as possible and, the more degraded the image is, the more difficult this task will be. The left column of figure 1 shows some examples of difficult eye images acquired in near infra-red.

The biometric authentication decision is based on a comparison between two such irises. To this end, the texture must be mapped into a dimensionless coordinate system to handle variability in the eye image such as pupil dilation. The most common choice for normalization is the rubber sheet model introduced by Daugman in [1]. Iris borders are modeled by two non-concentric circles and the texture is unwrapped with respect to these circles. Precision is a critical issue at this stage as small errors in circles' parameters estimation can dramatically decrease performance of the overall system as outlined by Proença et al. in [5]. Recent trends tend to extend circles to other parameter curves [6].

The purpose of the segmentation in an iris system is therefore twofold. The parametric contours of the iris region are used to unwrap the iris texture to produce the normalized image. Then identifying the pixels belonging to the iris in the eye image allows generating a so-called segmentation mask, which will be used to remove artifacts from the normalized image at the matching stage.

An important literature exists on iris segmentation. Amongst the most famous approaches, one can quote those using the spatio/temporal models [7], active contours [6] or geodesic active contours [8]. The common point between these approaches is that they rely on contour fittings from a gradient map. We would like to give a particular attention to the work of Pundlik et al. [9] who propose a different view, namely relying on an unsupervised segmentation of the eye, pupil, iris and background regions using pixel intensity values before detecting effective iris contours. To this end, they use a Hidden Markov Field (HMF) and a graph cut based energy minimization algorithm. Their approach is shown to be effective on non ideal images and compares favorably to other works from the State of The Art in terms of quality of the corresponding parametric contours.

In this paper we propose to follow the same trend and to explore different and more recent Markovian approaches, namely Triplet Markov Field (TMF). Introduced in [10], TMFs extend the classical HMFs and turn out be more efficient than the latter in different complex situations [11], [12], [13], [14]. Relying on these good results, our objective in this work, is to propose an implementation of TMF approaches for eye segmentation and to show on some challenging images extracted from two well-known iris databases ICE2005 [15] and ND-IRIS [16], the good behavior of TMF compared to HMF. Moreover, we will show that the precision of the normalization circles can be highly improved by the use of TMF segmentation, on a database of difficult images. This property will be very valuable in the construction of a complete iris recognition system. We will not only concentrate on the iris region detection but we will also assess the high quality of the detection of eyelashes and eye corners, which indicates also the high potential of this TMF based segmentation approach for periocular analysis.

This paper is organized as follows: Section 2 describes Hidden and Triplet Markov Fields. Section 3 presents their implementation in the context of iris segmentation. Experimental results on challenging iris images are provided and analyzed in Section 4. Finally, we conclude our paper and discuss future works in Section 5.

2. HIDDEN AND TRIPLET MARKOV MODELS

Let *S* be the set of pixels. A Hidden Markov field (HMF) is composed of two random fields $X = (X_s)_{s\in S}$ and $Y = (Y_s)_{s\in S}$, such as the variables X_s and Y_s take their values in a finite set of classes $\Omega = \{\omega_1, ..., \omega_K\}$ and the set of real numbers *R*, respectively. Let us assume that the distribution of X is a Gibbs distribution with respects to a neighboring system. Denoting by *C* the set of cliques (a clique being either a singleton or a set of pixels which are mutually neighbors), the distribution of X is then classically written:

$$p(x) = \gamma \exp[-W(x)], \tag{1}$$

with the "energy" $W(x)$ considered in this paper of the form:

$$W(x) = \sum_{(s,t)\in C} \alpha(1 - 2\delta(x_s, x_t)), \tag{2}$$

where $\delta(x_s, x_t) = 0$ for $x_s = x_t$, and $\delta(x_s, x_t) = 1$ for $x_s \neq x_t$. X is then a Markov Field with respect to four nearest neighbors. The distribution of Y conditional on X is classically given by:

$$p(y|x) = \prod_{s\in S} p(y_s|x_s) \tag{3}$$

And thus the HMF's distribution is

$$\begin{aligned} p(x, y) &= p(x)p(y|x) \\ &= \gamma \exp\left[-W(x) + \sum_{s\in S} Log(p(y_s|x_s))\right] \end{aligned} \tag{4}$$

Such a model allows sampling of realizations of X according to the posterior distribution $p(x|y)$. The latter makes feasible the estimation of the posterior margins $p(x_s|y)$ which leads to the Bayesian method Maximum Posterior Modes (MPM) we use in this paper to recover X from $Y = y$.

To introduce the triplet Markov Fields (TMF) used in this paper we consider two random fields $X = (X_s)_{s\in S}$, $Y = (Y_s)_{s\in S}$ as above, and we introduce a third random field $U = (U_s)_{s\in S}$ in which one each U_s takes its values in $\Lambda = \{a, b\}$. We then assume that the couple (X, U) is Markovian. As above, the distribution $p(x, u)$ is then written as:

$$p(x, u) = \gamma \exp[-W(x, u)] \tag{5}$$

with $W(x, u)$ used in this paper being of the form:

$$\begin{aligned} W(x, u) = & \sum_{(s,t)\in C_H} \alpha_H^1 (1 - 2\delta(x_s, x_t)) \\ & - (\alpha_{aH}^2 \delta^*(u_s, u_t, a) + \alpha_{bH}^2 \delta^*(u_s, u_t, b))(1 - \delta(x_s, x_t)) \\ & + \sum_{(s,t)\in C_V} \alpha_V^1 (1 - 2\delta(x_s, x_t)) \\ & - (\alpha_{aV}^2 \delta^*(u_s, u_t, a) + \alpha_{bV}^2 \delta^*(u_s, u_t, b))(1 - \delta(x_s, x_t)) \end{aligned} \tag{6}$$

where C_H is the set of horizontal cliques, C_V is the set of vertical cliques, $\delta^*(u_s, u_t, a) = 1$ for $u_s = u_t = a$, and $\delta^*(u_s, u_t, a) = 0$ otherwise, and $\delta^*(u_s, u_t, b) = 1$ for $u_s = u_t = b$, and $\delta^*(u_s, u_t, b) = 0$ otherwise.

Assuming that $p(y|x, u) = \prod_{s\in S} p(y_s|x_s)$, the distribution $p(x, u, y)$ is finally given by:

$$\begin{aligned} p(x, u, y) &= p(x, u)p(y|x, u) \\ &= \gamma \exp\left[-W(x, u) + \sum_{s\in S} Log(p(y_s|x_s))\right] \end{aligned} \tag{7}$$

As in the classical HMM model, (X, U) can be recovered from $Y = y$ by using $p(x_s|y)$, which are here obtained from $p(x_s, u_s|y)$. Details can be seen in [11].

3. IRIS SEGMENTATION

In this Section we explain how we have implemented the two models described above to the segmentation of iris. The question can be summed up as how we can define the 2 processes X and Y mentioned in Section 2 in the context of grey-level pixels images. In this context, for each pixel $s \in S$, the searched x_s will be in the set of classes "pupil", "iris", "eyelashes".., and so on. Note that this segmentation is non-supervised and that the number of classes is fixed a priori.

Thus, the problem of image segmentation using Markovian modeling is to estimate the unobservable realization $X = x$ from the observed one $Y = y$. Realizations of Y are the illumination intensity and the searched realizations of X is the segmentation result, which is an image of classes ideally corresponding to "pupil", "iris", "eyelashes" and "background". Therefore, for each $s \in S$, the problem is to propose an estimated $\hat{x}_s \in \Omega$ that would be optimal in some sense. To this end, we have chosen the Maximum Posterior Mode (MPM) segmentation method commonly used in HMF context and which produces an estimated $\hat{X} = \hat{x} = (\hat{x}_s)_{s \in S}$, with $\hat{x}_s = \arg\max_{\omega \in \Omega} p(x_s = \omega | y)$, where $p(x_s = \omega | y)$ are estimated from the sampled realizations of X according to $p(x|y)$, which is possible because of its Markovianity.

Moreover for an automatic processing, a parameter estimation technique is needed. We use the "iterative conditional estimation" (ICE), whose principle is to consider an estimator $\hat{\theta} = \hat{\theta}(X,Y)$ of θ from the complete data (X,Y) and to define the iterations $\theta^{q+1} = E_{\theta^q}[\hat{\theta}(X,Y) | Y = y]$, see [11] for details.

4. EXPERIMENTAL RESULTS

In this Section, we first show the quality of the segmentation obtained by the proposed TMF method compared to HMF for iris and periocular segmentation. Then, we demonstrate the improvement provided by the use of TMF region segmentation on the precision of the detection of the pupil and iris circles.

4.1. TMF vs. HMF methods for eye segmentation

To evaluate the contribution of the TMF approach for eye segmentation, we performed two segmentations: one with a HMF model of the kind of the model proposed by Pundlik et al. in [9] and the other with TMF model, which extends the HMF model used. To this end, we select non-ideal and difficult images for iris segmentation from two databases ICE2005 and ND-IRIS and we compare the segmented images resulting from each method.

The left, middle and right columns of Figure 1 represent respectively the original eye image and corresponding segmentations in 4 classes with HMF and TMF without any preprocessing. These original images are of poor quality. For example, the original images at the first and second row of Figure 1 suffer from low contrast. In this case, HMF cannot distinguish the pupil and the iris unlike TMF, which segments them correctly as two distinct classes. In the third and fourth rows, original images are highly blurred. Despite this, TMF segments correctly the pupil and the iris; moreover eyelashes are finely detected contrary to HMF segmentation. The original image of the fifth row presents strong occlusions (eyelashes), shadow and variation of illumination. The TMF segmentation is largely better than HMF one. The iris is well separated from the sclera and eyelashes are distinctly detected which is very useful for producing a good mask allowing comparing only iris texture in the matching stage.

Although the TMF model improves globally the eye segmentation, the method remains sensitive to illumination artifacts which may lead to wrong iris segmentation as shown in the two last rows of Figure 1. The use of more

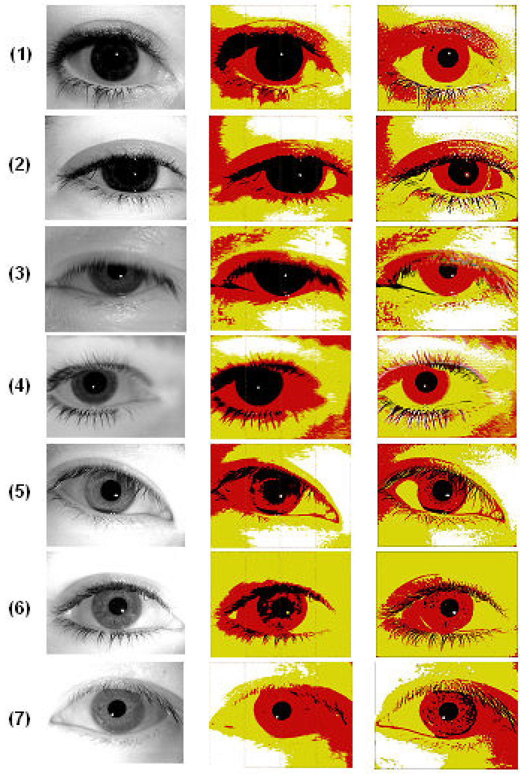

Fig. 1. Eye segmentation of non-ideal images (left column) using HMF (middle column) and TMF (right column) methods.

complex TMF, obtained for example by taking richer set $\Lambda = \{a, b\}$, would possibly improve these results. However, we note that the TMF segments correctly and finely the shape of the eye which is very interesting in practice. As shown in [4], the periocular region contains discriminant information which can be fused with the iris texture to improve performance of an overall recognition system in non-ideal situations. The shape of the intern corner of the eye could be also used for right-left eye classification [17].

4.2. Accuracy of normalization circles

As previously said in the introduction, finding precise parameters of the iris normalization contours (pupil and iris) is very important in iris recognition. Small errors in such parameters lead to strong degradations in performance of the recognition system. In this work, we limit ourselves to circular boundaries and the parameters of the normalization circles (center and radius of both pupil and iris) are provided by the segmentation block of OSIRIS_V4 which uses a Viterbi algorithm and least-squares based circle fitting methods applied on a gradient map to estimate these parameters [18]. This approach has been shown to produce recognition results which compare favorably to the State of the Art. We evaluated the accuracy of the normalization circles on a subset of images (236 images) selected manually from ICE2005 database. These images suffer from strong occlusions (eyelashes and eyelids), high blur and illumination problems. We made a manual segmentation of this dataset by defining the coordinates of both inner and outer circles. This manual segmentation was used as ground truth to compare the parameters of the circles given by OSIRIS_V4 on the original images and on the images segmented in 4 classes by the TMF. Figure 2 illustrates, on a given image, two cases of normalization circles obtained with TMF (right) and without (left).

For each method of segmentation, the errors on the pupil and the iris center are computed as the Euclidian distance between the estimated center and the ground truth center. The errors are normalized with respect to pupil or iris radius. Figure 4 shows the cumulative histogram of errors in pixels on the centers detected by OSIRIS_V4 with original and TMF-segmented images for the pupil and the iris. From these results, one can infer that using the TMF segmentation, 91% and 92% of the images have respectively a normalized error on pupil and iris center of less than 0.1. However only 76% and 90% of the images have respectively a normalized error of less than 0.1 on pupil and iris center without using TMF segmentation. On Figure 3, we notice on the cumulative histogram of these errors an overall improvement in the localization of the center of both pupil and iris with the TMF segmentation. This is more clear for the pupil circle center than for the iris' one.

Figure 4 shows the histogram of the errors in pixels of the pupil centers with and without TMF segmentation. It is observed that the pupil center error distribution shifts toward zero with TMF segmentation, which indicates more accuracy in the normalization circles. Moreover we note an improvement of roughly 50% for the value of the pupil center errors corresponding at the pick of the 2 distributions (from 0.055 versus 0.095).

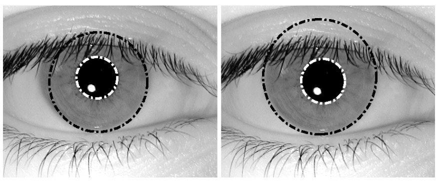

Fig. 2. Two different localizations of the normalization circles for the same eye image: wrong (grey-level pixel based) on the left; good (TMF-based) on the right.

5. CONCLUSION

In this paper, we have proposed an implementation of a Triplet Markov Field model for eye segmentation. We have shown on some challenging images extracted from two well-known iris databases, the good behavior of TMF

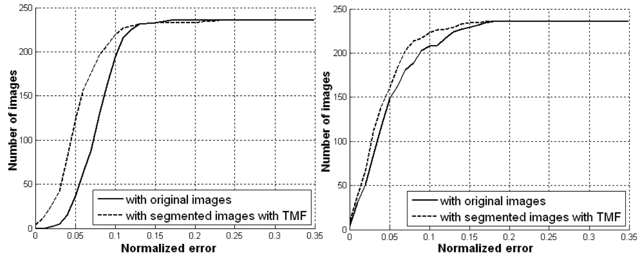

Fig. 3: Cumulative histogram of errors in pixels of the centers of pupil (left) and iris (right) circles detected by OSIRIS_V4 on original and segmented TMF images.

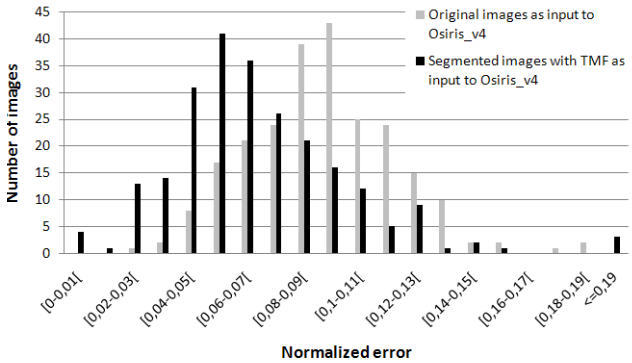

Fig. 4: Histogram of pupil center normalized errors for circles detected by OSIRIS_V4 on original and segmented TMF images.

compared to traditional Hidden Markov Field model. In particular, we have observed that despite of defaults such as blur, low contrast, large occlusions, the simple TMF used was able to produce a fine segmentation of the iris and moreover a very accurate segmentation of the eyelashes, eyelids, eye corners where the HMF fails. The present implementation is still sensitive to illumination variations and one of our perspectives is therefore to extend the Triplet Markov Field in order to explicitly model the shadow as is made in [19] in the framework of Triplet Markov chains [20]. Moreover, we have shown, on a database of 236 irises presenting heavy degradations, that the normalization circles fitted on the TMF-based segmented image have a better precision that those fitted on the original grey-level image. This property will be very valuable in the construction of a complete iris recognition system as big improvements in terms of recognition rates can therefore be expected on large databases containing many images of low quality. Moreover this approach will also be very helpful in the context of periocular detection and recognition. Experiments for confirming these points will be the subject of our further works.

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