POSTURE RECOGNITION USING CORRELATION FILTER CLASSIFIER

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ABSTRACT

In this paper, we described an innovative methodology of recognizing four main postures namely standing, sitting, bending and lying position using correlation filter particularly Unconstrained Minimum Average Correlation Energy (UMACE). Initial results prove the UMACE filters offer significant potential in posture recognition task. The filter was subjected to a challenging task to recognize human posture without any restriction on the gender, clothing and posture variations. Classification outcome confirm the UMACE filter performs remarkably well with an average accuracy of 85%.

Keywords: Posture Recognition, correlation filter, UMACE filter, PSR.

1. INTRODUCTION

One common machine vision application is to edify computer to distinguish information and dataset automatically, to save the man-hours or boredom attributed to these tasks. Recognition of human posture is a very challenging problem. The importance of human posture recognition or classification is evident by the increasing requirement of machines that are able to interact intelligently and effortlessly with a human inhabited environment. It could be deemed as the first stage towards developing applications in real time surveillance, pedestrian detection and gait recognition. This will take the capability of machines into 'understanding human' domain.

On the other hand, the potential of advanced correlation filters have been explored recently and they have progress into very effective algorithms for pattern recognition applications specifically biometrics verification [7] [9] [10] [13] & [14]. For instance, Savvides and Kumar [10] examined the performance of advanced correlation filters for face authentication. The results are based on the illumination subsets of the CMU PIE (Carnegie Mellon University Pose, Illumination, and Expression) database. They also presented methods that reduce the memory requirements of these filters to run on limited computational resources including computationally efficient methods of synthesizing these filters. Further, they described an online training algorithm implemented on a face verification system for synthesizing correlation filters from a video stream to handle pose and scale variations. Their system also uses an efficient scheme to perform face localization within the current framework during the authentication stage.

Another related work is by Jingu Heo et al [9] on the evaluation of face recognition performance based on visual and thermal infrared (IR) face images using advanced correlation filter methods. They used MACE and OTSDF (Optimal Tradeoff Synthetic Discriminant Function) filters and achieved better performance over commercial face recognition algorithms such as FaceIt®.Their work proved that correlation filters performed very well when the face images are of significantly low resolution and could be applied in human identification at a distance (HID). They also described in detail a fully automated way of eyeglass detection and removal in thermal images resulting in a significant increase in thermal face recognition performance.

K Venkataramani et al [13] also evaluated the performance of composite correlation filters in fingerprint verification for access control applications. They focused in obtaining digital live-scan fingerprints from sensors, rather than the inked fingerprints usually used in criminal identification. The NIST Special Database 24, obtained from an optical fingerprint sensor, was used to evaluate the performance of fingerprint verification in the presence of distortion. Their results showed that unconstrained filter was a good choice since it can be incrementally updated to reduce complexity demonstrating the distortion tolerance potential of correlation filters and performed reasonably well even with low resolution images. On the other hand, Pablo Henning et al [7] introduced the application of correlation filter classifiers for palmprint identification and verification. They described how the extraction of an appropriate region of interest in the palmprint surface could be used to design correlation filters that accomplish 100% recognition on a database of 50 persons. Recently, Chong et al [14] developed a private biometrics formulation that is based on the concealment of random kernel and the iris images to synthesize a MACE filter for iris authentication. The purpose was to provide private biometrics realization in iris authentication in which biometric template can be reissued once it was compromised. The proposed method was able to decrease the computational load by reducing the filter size and thus, improved the authentication rate significantly.

In this study, in an attempt to further reveal the efficiency and robustness of correlation filters, we investigate the possible use of advanced correlation filters specifically UMACE in our posture recognition system by illustrating the additional abilities of UMACE in recognizing posture images. The main advantage of this method over previous approaches of posture recognition [1] [2] [3] [4] & [5] is that no feature extraction stage is involved since the image pixels are the input domain for training the filters. This particular property of correlation filters has been proven effective in recognition and classification [6] [7]. The paper is organized as follows. Section 2 describes the methodology, Section 3 includes a brief background on UMACE and Section 4 evaluates and discusses the performance of UMACE filter. Finally, in Section 5 we conclude our findings.

2. METHODOLOGY

Firstly, four categories of human postures namely standing, bending, sitting and lying position were chosen for classification purpose. The system implementation includes background subtraction and silhouette extraction. In this work, we assume a static background and the background subtraction are achieved by thresholding the difference between the current frame and the static background image. In doing so, a human silhouette is extracted. Further, advanced correlation filter will feat as the posture classification system. Advanced correlation filters also known as composite filters, are the family of correlation-based classifiers. A template is used to correlate a test image and look for a sharp peak in the output plane that ideally resembles an impulse. This will be the evident characteristic of correlation outputs corresponding to images of the correct posture. In contrast, when a different posture image is correlated, the output shape does not contain a well-defined peak and it indicates that the image is a false or incorrect posture. This concept is illustrated in Figure 1.

The performance of such correlation templates depends highly on the set of images used for computing the template. Indeed, advanced correlation filters have been thoroughly studied in the last two decades, and they have evolved into very effective algorithms for pattern recognition applications [6] [7] & [8]. Advanced correlation filters can be designed to accommodate the intrinsic amplitude variability of the images in the training set while being tolerant to noise pervading the images [9][10].

In our experiments, 150 images of size 64×64, for each category of the four main postures are chosen as our database to evaluate the performance of UMACE for posture recognition. We first applied 3 training images comprising of the front and side posture views in order to synthesis the UMACE filter of each posture. This process continues as the number of training images are increased in step of 3 each time until reaching 15 images. To evaluate the performance of each posture, cross correlations of all the images in the dataset were computed using each posture UMACE filter resulting in 150-15=135 correlation outputs corresponding to true class posture and 150 x 3 = 450 false class postures. The corresponding PSRs were then measured, recorded and evaluated.

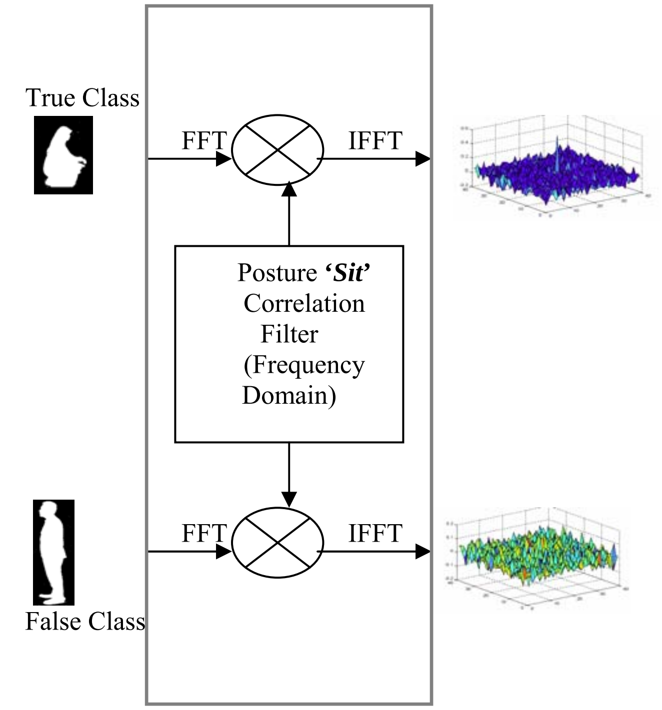

Figure 1: Application of advanced correlation filter in posture recognition

3. OVERVIEW OF COMPOSITE FILTERS

The fundamental motivation for designing correlation filters was driven by distortion invariant optical pattern recognition. Hester and Casasent [11] introduced the synthetic discriminant function (SDF) approach for this purpose in 1980. SDF is a linear combination of matched spatial filters whereby the weights are chosen so that the correlation outputs corresponding to the training images will yield equivalent correlation peak values at the origin. The drawback of the ECP SDF is twofold. First, it cannot tolerate significant input noise. Second, ECP SDF has no built-in shift-invariance capability. Thus, shifts in the input target are replicated in the correlation output. Nevertheless, the SDF method has deeply influenced the current design of advanced correlation filters although the idea was actually introduced more than twenty years ago. To achieve robustness to noise, Kumar [12] introduced the MVSDF (Minimum Variance Synthetic Discriminant Function). There are two drawbacks to this method. The first is that the MVSDF also controls only one point in the correlation map, just like the ECP SDF. The second is that the variance of the noise matrix must be made known beforehand in order to design the filter.

However, even if the latter is known exactly, MVSDF is impractical because it requires inverting a large noise covariance matrix [12]. The MACE (Minimum Average Correlation Energy) filter was an attempt to control the entire correlation plane. Kumar et al [12] reduced correlation function levels at all points except at the origin of the correlation plane and thereby obtained a very sharp correlation peak. However, MACE filters often suffer from two main drawbacks. Firstly, there is again no built-in immunity to noise. Secondly, the MACE filter is often excessively sensitive to intra-class variations. Studies have shown that hard constraints on correlation values at the origin are not only unnecessary but can be counterproductive [12]. Hence, unconstrained correlation (UC) filters were introduced.

3.1 UMACE (Unconstrained Minimum Average Correlation Energy) Filters

As mentioned, we have implemented one of the special UC filters, called UMACE short for Unconstrained Minimum Average Correlation Energy. UMACE is another variant of the MACE filter [10] and instead of imposing a hard constraint on the origin of the correlation plane, its height at the origin is free to increase according to the test data. The optimized filter equation is given as:

$$H = D^{-1}\,\mathbf{m} \tag{1}$$

where **m** is a column vector containing the average of the 2D Fourier transforms of the training images. UMACE filters are computationally more attractive as they require the inversion of only a diagonal matrix. Noise tolerance can be built in to the filters as described in [10]. This is done by substituting **D** with **D'** and **D'**= α**D** + sqrt (1-α^2)**C**, where **C** is a diagonal matrix containing the noise power spectral density. For white noise, **C** is the identity matrix and α range from 0 to 1 and is chosen to trade-off noise tolerance for discrimination.

3.2 Peak-to-Sidelobe Ratio (PSR)

For a well-designed correlation filter, we expect to see prominent peaks in the correlation output for true class images. The correlation output of a false class posture has no discernible peak. Typically, the peak-to-sidelobe ratio (PSR) is used as a performance measure for the sharpness of the correlation peak. PSRs are typically large for true class and small for false category. Thus, the PSR is used to evaluate the degree of similarity of correlation planes [10][13]. The significance of the

PSR is that it measures the sharpness of the correlation function.

4. PERFORMANCE OF UMACE

In this experiment, UMACE filter is applied to evaluate its performance and capability in posture recognition. The PSR performances in each posture class are determined. Figure 2 illustrates the UMACE performances respectively with 15 training images. As can be seen, UMACE filter produces an acceptable significant margin that discriminates the true class posture and the false category. Experimental results showed that by increasing the number of training images has helped increase the margin between the true class and the false class posture and thus, giving better discriminating ability. It was also observed that the variance of the false class is reduced as the number of training images is increased. In the verification stage, the following three quantities were used to select the proper threshold namely False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER). For a given verification PSR threshold θ_v for a class, the performance can be measured by the false acceptance rate (FAR) and false rejection rate (FRR), defined as follows:

When FAR and FRR are equal, the common value

$$\text{FAR} = \frac{\#\text{ of false posture images having PSR} > \theta_v}{\text{total number of false posture images}}$$

$$\text{FRR} = \frac{\#\text{ of true posture images having PSR} < \theta_v}{\text{total number of true posture images}}$$

is referred to as equal error rate (EER). Next, each posture in the database was verified against every other posture. For a particular filter, all of the false class postures (150 x 3 = 450) and true class posture (150 - number of training images used) criterion scores were obtained. Table 1 displays the average EER for each posture using 3 images and then being increased in step of 3 until 21 images. It is noted that at 12 training images offered almost equal EER performances even if the number of training images is increased. Therefore we conclude that 12 training images are acceptable as our templates.

Subsequently, the threshold value to be selected for each posture is determined from the performance curves for all postures as illustrated in Figure 3. Thus, the lower the EER, the superior the overall performance of the verification system. It is obvious from the results that UMACE filter could separate the true class posture from the false category particularly for standing and lying down postures with recognition results of 96.2% and 93.6% respectively. Some samples correlation outputs of the postures are presented in Figure 4. The best testing model that matches the training image will have a large PSR value. The PSR value reflects the UMACE filters' ability to recognize and verify similarity between postures. It can be realized in Figure 4 that the true class posture has higher PSR than the false category.

5. CONCLUSIONS

The performance of advanced correlation filters in particular UMACE, for posture verification is presented. Based on the results obtained, it is found that the UMACE filter is robust with respect to variation in postures. It was determined that using 12 training images, the UMACE filters are capable of discriminating over 90% of the true class posture from the false profile namely for the standing and lying position posture where as for sitting and bending categories it obtained above 80% correct classification. It should be noted that the postures database comprises of various position for both gender without clothing restriction. Therefore, the recognition outcomes are considered remarkable. These results are promising and demonstrated the potential use of advanced correlation filters as an interesting option for posture recognition.

Further work includes evaluating the effect and performance of different image regions and using multiple filters for training images. Accordingly, incremental updating of filters could also be considered for memory reduction, as space is a constraint in most recognition system. Hence only a few training images are involved at a time. The performance of other correlation filters such as Maximum Average Correlation Height (MACH), Distance Classification Correlation Filter (DCCF) filters could also be experimented for posture verification system.

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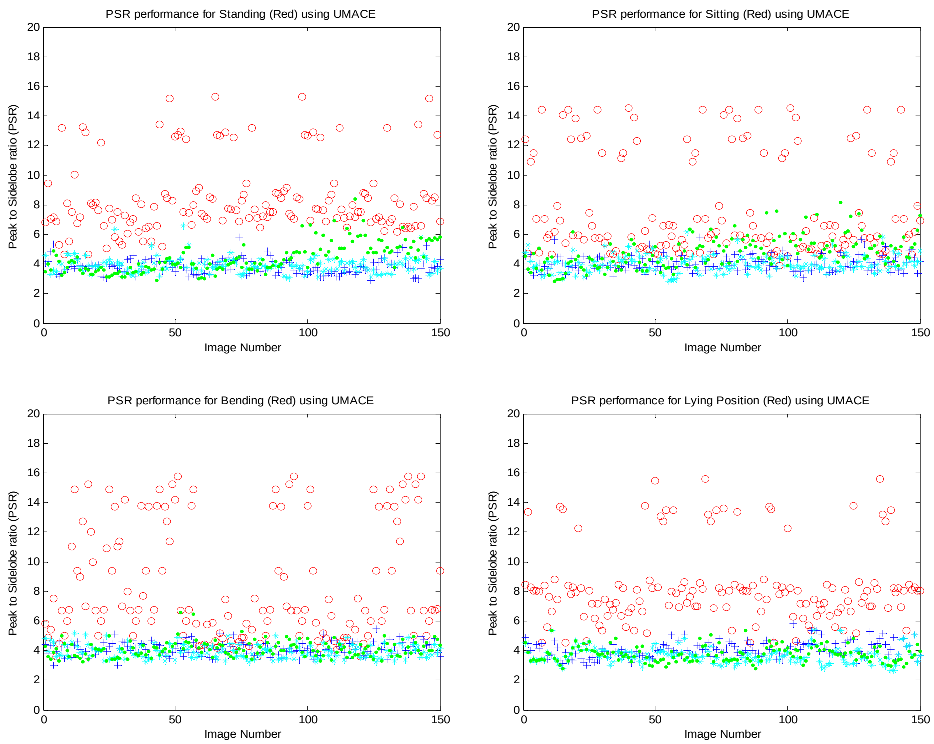


Figure 2: PSR score for each class posture using UMACE filter

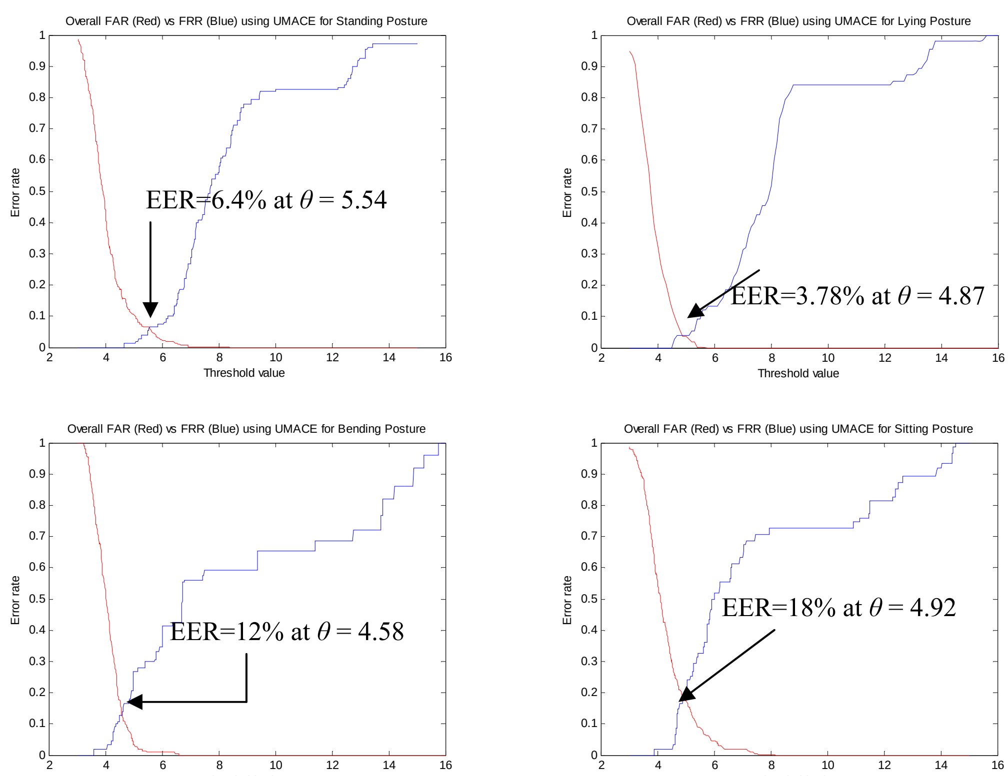
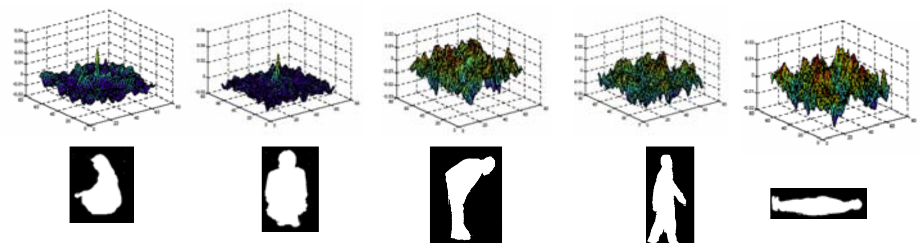
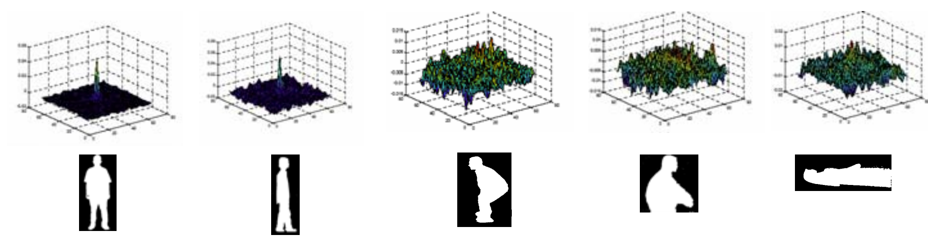


Figure 3: FAR vs. threshold and FRR vs. threshold. ERR is obtained by adjusting FAR vs. FRR.

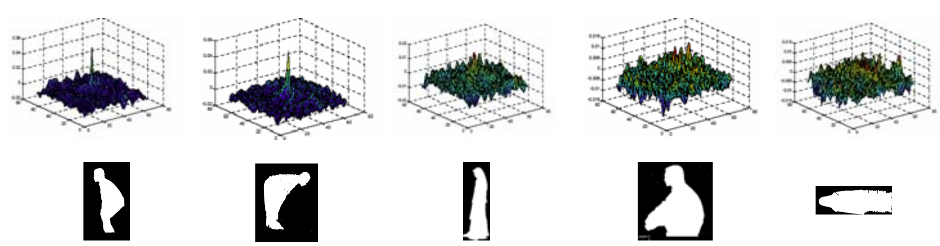
	TRAINING IMAGE	1True Class	TESTING IMAGE 3 False Classes		



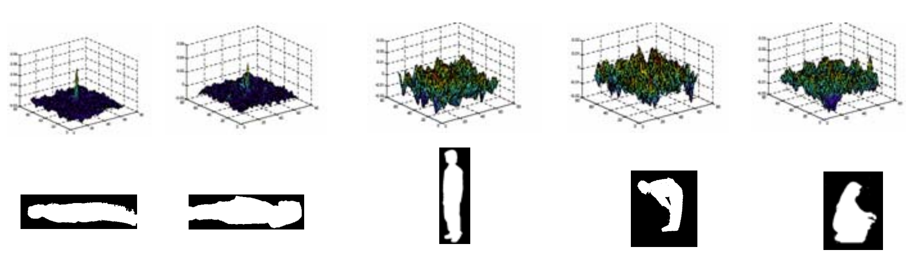
PSR(SIT)	20	15	2	4	3



PSR (STAND)	15	10	3	3	2



PSR (BEND)	20	10	4	2	2



PSR (LYING)	21	17	1	2	3

Figure 4: Correlation outputs for each posture using UMACE filter with 12 training images.

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