Contourlet Based Image Compression for Wireless Communication in Face Recognition System

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***Abstract*—This paper proposes to use Contourlet transform for image compression and feature extraction for wireless face recognition system. The properties of face images and face recognition techniques are incorporated into the design of wireless transmission for such a system. The reasons for utilizing contourlet transform are two-folded. Firstly, in face recognition, the edge information is crucial in deriving features, and the edges within a face image are not just horizontal or vertical. When the coefficients are transmitted through the fading channel, the reconstruction from the Stein-thresholded noisy coefficients by contourlet achieves less mean square error than by wavelet. Secondly, when the network resources limit the transmission of full-set coefficients, the lower band coefficients can serve as a scaled-down version of the face image, for a coarser face recognition as screening. A prioritized transmission of the coefficients take full advantage of the wireless channel. Simulation shows that the wireless face recognition system works as well as a wired one, while gaining the cost efficiency, and the flexibility in deployment. An interesting phenomenon is discovered on FERET database that when the transmission error rate is increased linearly, the recognition performance degradation is not linear; instead, the performance stays the same for a large range of error rates, which illustrates that contourlet based face recognition system can tolerate the transmission error up to some threshold.**

***Index Terms*—contourlet, face recognition, compression, wireless communication**

I. Introduction

Image processing for wireless transmission is a challenging task, because of the amount of image data that need to be processed in real time, the restriction of transmission bandwidth, and other limited resources of the wireless network. Wireless face recognition is a particular interesting application of image processing for communications, where face recognition is implemented at the application layer, and a customized processing on face images helps correct or tolerate the transmission errors at the lower layers, namely the network layer, the MAC layer, and the physical layer. A face recognition system benefits from flexible wireless transmission, and the communication issues such as noise deduction and efficient transmission should be considered in the design of a wireless face recognition system. The first resort to improve transmission efficiency while maintaining data fidelity is by image compression and relevant denoising scheme. The second resort to improve data processing efficiency is by coefficients domain processing for face recognition.

There's a rich history on the development of transforms for image compression and denoising, such as by discrete cosine transform (DCT) or discrete wavelet transform (DWT). As an attempt to represent the curves more efficiently, Starck, Candès and Donoho develop the continuous curvelet transform [1] in polar coordinates. M. N. Do and M. Vetterli develop the contourlet in the discrete form [2], directly on the regular grids. The contourlet construction provides a space-domain multiresolution scheme that offers flexible refinement for both the spatial resolution and the angular resolution.

As to the applications of the coutourlet transform, Ramin Eslami and Hayder Radha [3] revised it by cycle spinning to denoise images, such as the received images at the end of the wireless channel. Yan et al. uses the contourlet transform as a coding scheme for images, and the contourlet coefficients are transmitted through the wireless fading channel [4]. Simulation shows that the mean square error (MSE) and the visual effect for both the contourlet transform and the wavelet transform are comparable. Contourlet transform works better when the edges are not just horizontal or vertical.

In face recognition, edge information is crucial in deriving features, and the edges within a face image are not just horizontal or vertical. Hence, image compression is implemented by contourlets rather than wavelets. Contourlet supports progressive data compression/expansion. Meanwhile, in the wireless environment, errors are bound to happen in the data stream. Based on the varying density of information in the data stream, a prioritized transmission scheme is utilized to ensure the transmission accuracy, and the transmission of coefficients works robustly for image reconstruction.

Nevertheless, in face recognition, image reconstruction is not required, unless the end user wants to see what images are captured from the image sensors. In order to further improve data processing efficiency, we propose to implement face recognition in contourlet coefficient domain, instead of in image domain. There have been several inspiring techniques on transform domain face recognition. Kohir and Desai utilize DCT transform and hidden Markov model (HMM) to do face recognition [5], where DCT is applied on successively overlapping regions of a face image. Wang and Feng also present an approach for face recognition based on HMM in DCT compressed domain[6]. Marcus utilizes DCT transform and multi-layer perception neural network to do face recognition, and achieves higher accuracy than PCA based method

[7]. Travieso, Alonso and Ferrer implement DCT, DFT, and DWT respectively, with linear, kernel or RBF SVM to do face recognition [8].

The open standard image compression utilizes DCT in JPEG and DWT in JPEG2000, and the impact of image compression in face recognition is studied in literature. Eickeler, Müller and Rigoll apply statistical methods based on Pseudo 2-D Hidden Markov Models and DCT features to recognize JPEG face images in the compressed domain with success[9]. Delac and Grgic et al. carry out face recognition in compressed JPEG2000 domain without significant performance drop[10]. They also find out that while the images compressed to 0.3 bpp (bits per pixel) are visually significantly distorted, the recognition results are almost statistically indistinguishable from the results achieved by using uncompressed images [11]. This result is interestingly consistent with our study on the effect of transmission error on the recognition accuracy, as is discussed in section IV.

Besides image compression, other transformations can be applied on face images, such as for the purpose of feature extraction. Foon, Pang, Jin and Ling combine DWT with Zernike moments (ZM) as a feature vector for face recognition [12]. Zhang, Leung and Gao combine kernel associative memory (KAM) and Gabor wavelet transform. KAM captures the important intra-class variations in Gabor transforms [13]. Zhang and Huang, et al. utilize curvelet to transform face images and apply SVM classifier for face recognition [14], and their simulation results show that curvelet works more accurate than wavelet based method. However, curvelet is a continuous transform. Approximation of it on a digital image violates its mathematical properties. In contrast, contourlet is a discrete transform defined on the regular grids, which does not have the limitations of curvelet. This paper furthers the study of transform domain face recognition based on contourlets, and it analyzes the efficiency of applying face recognition in the transform domain instead of in the image domain.

The rest of this paper is organized as follows: Section II gives a brief introduction to contourlet transform, wireless channel, and the subspace-based modular processing technique with fusion for face recognition. Section III describes the transmission of the data within the wireless network and the recognition in the coefficient domain. Section IV provides the simulation result of the proposed face image processing for communication. Section V concludes the paper and indicates potential future work.

II. Wireless Face Recognition System

Face recognition has been gradually accepted by the general public as a viable biometric verification method. Face recognition is an important biometric in security system for its speed, non-contacting property and its increasing accuracy. Wirelessly constructed face recognition system is more flexible in watching the dynamic region of interest, in the specific deployment of cameras and in sharing the face database. In wired face recognition system, the data transmission is usually reliable, and the goal of a successful wireless face recognition system is to keep up with the performance of a wired system while keeping the convenience of a wireless system. What's more, being integrated into a wireless network, face recognition enhances the functionality of the wireless network. Zaeri, Mokhtarian and Cherri discuss face recognition for wireless surveillance systems [15]. Ikdong, Jaechang, Jason and Wayne implement a wireless face recognition system based on ZigBee and Eigenface with low power consumption [16].

Face recognition includes verification and identification. Face verification is one-to-one matching, which is relatively easy and realized in mobile phone or computer login verification by Omron, Oki Electric, FaceCode, etc. Face identification is one-to-many matching, which is more complex, since a huge database needs to be compared, and *curse of dimensionality* phenomenon happens. It's envisioned in the future that face identification can be also carried out on a mobile terminal unit, which connects to a wireless network to implement face recognition task in a distributed and collaborative way. The challenges in realizing this envision include *(1)* A wireless face recognition system requires considerable energy, computing and bandwidth for image acquisition, processing, and transmission. *(2)* Face recognition techniques need to be more robust and accurate. In this paper, we make a few steps towards solving this problem: The first challenge is addressed by image compression by contourlet transform. The second challenge is addressed by a robust face recognition technique, namely subspace-based modular processing with score and decision level fusion. The fusion in image domain is shown to be superior to using either the whole face or modules alone [17], and in this paper, fusion in coefficient domain shows improvement as well.

A. The Contourlet Transform

The contourlet transform is a true 2D transform defined in the discrete form to capture the edge information in all directions. The mathematical formulation and the applications of the contourlets are detailed by Minh N. Do [18]. Conceptually, the contourlet transform first decomposes the image by Laplacian pyramid to detect the edges in all scales, and then it applies directional filter bank to link point discontinuities into linear structure. Practically, Do, et al. propose to use pseudo inverse structure for robust and simple reconstruction[2]. In pseudo inverse, the directional filter bank is replaced by an equivalent operation to shear the image by certain angles and then pass the sheared image through one vertical and one horizontal fan filter. The illustration of contourlet transform and reconstruction is shown in the transmitter and receiver, respectively, in Fig. 1.

B. Wireless Fading Channel

Contourlet transform is not only efficient in capturing edge information, but also robust in denoising, which is desirable for wireless transmission. Eslami, et al. [3], Starck, et al. [1] implement contourlet transform on noise-contaminated images, apply hard-thresholding on coefficients, and then reconstruct the images from the thresholded coefficients. The denoising performance is very good in the sense of MSE and visual effect. In this paper, a different application of contourlet is discussed: The images are encoded into contourlet coefficients, and then the contourlet coefficients are transmitted through the wireless channel, instead of the original images. In particular, the left half of Fig. 1 is implemented in the transmitter (Tx), and the right half of Fig. 1 is implemented in the receiver (Rx). The fading channel (Ch) distorts the original contourlet coefficients y_0 and y_1 to be $\tilde{y_0}$ and $\tilde{y_1}$. At the receiver end, the reconstruction directly from the received coefficients is a noisy recovery of the original image. If the received coefficients are hard thresholded or processed by other delicate denoising schemes, the reconstructed image is a denoised one. The wireless channel is assumed to be Rayleigh flat and slow fading. The segment between the dashed line in Fig. 1 is modeled as a signal scaled by Rayleigh envelop and contaminated by white Gaussion noise. The variation of such a wireless network is mainly due to the small scale fading.

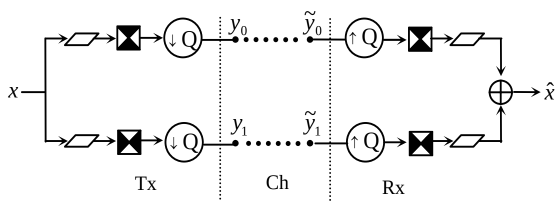

Fig. 1. Contourlet transform used in wireless image transmission

C. Face Recognition based on Subspace-based Modular Processing with Fusion

In face recognition, the training images are pre-processed, mean extracted, vectorized and paralleled to construct a single matrix. The covariance matrix of this training matrix is highly singular because the number of features is much less than the dimension of the images. PCA based Eigenface method utilizes the range space of the covariance matrix of the training database to fully represent the training data[19], [20]. In LDA based methods, within class scatter is defined as the covariance matrix of the different images of the same person. Between class scatter is defined as the covariance matrix of the differences between different subjects, where the means of different subjects are used as the representations of those subjects. Fisherface method applies PCA first to discard the null space of the within class scatter to avoid the singularity problem and then utilizes the range space of the between class scatter[21]. But the null space of the within class scatter is also shown to be informative in discrimination, so Chen, et al. [22] and Yu, et al. [23] proposed direct LDA methods (D-LDA) to implement the LDA method on the original high dimensional space without the PCA reduction. However, techniques by Chen, et al. may get intractable when the within class scatter is too big, and techniques by Yu, et al. may suffer from the possible singularity of the within class scatter, where a heuristic constant ϵ is introduced to control this situation, but the selection of ϵ is subjective. Lotlikar, et al. [24] introduced the weighting functions to make the closer classes more separated in outputs, and it's called fractional-step LDA method (F-LDA). Lu, et al. [25] combines the D-LDA method and F-LDA method, and proposes DF-LDA method, which avoids the singularity problem of the within class scatter with variation on the optimization objective to simplify the calculation while keeping the performance. DF-LDA technique is applied in this paper, which utilizes the null space of the within class scatter and the range space of the between class scatter.

Besides subspace based DF-LDA technique, modular processing is also applied in this paper. The modules are segmented eyes, nose, mouth, etc., which are treated as independent objects for classification. Face recognition, as one of the non-contact, less-intrusive biometrics, is irreplaceable in certain situations. However, other biometrics may not always be available for multimodal biometrics. It is desirable that diversity is implemented in face recognition alone. The modules are utilized to derive the Eigenparts or DFLDAparts by the same algorithms used on the whole face. Since the images of modules are directly segmented from the whole face image, the fused result from multiple classifiers emphasizes the features existent in both the Eigenface and Eigenparts, or LDAface and LDAparts. The emphasis on these features improves identification because certain individuals have very distinguishing eyes, nose or mouth, and some local modules are not varying much as other modules of the face. From a single test image, five similarity scores are derived for each classifier using the stored templates. The similarity scores are real numbers indicating their relative degree of similarity. The *score* from each classifier can be normalized and combined for a final score. Based on the similarity scores, each classifier can decide on which subject the test image is closest to. In some applications, it is not only the most similar identity, but also the runners up that are in concern. The classifiers maintain the rankings of several potential identities. The ranking of the potential identity indices is called a *decision*, which is a categorical number. The fusion of modules can then be done at either score level or decision level.

III. Transmission of Contourlet Coefficients

A. Image Recovery and Denoising

Fading channel introduces noises, and since the contourlet transform packs the information of the original image into a compact form with most of the coefficients close to zero and only a small portion of the coefficients being significant, the transmission of contourlet coefficients helps in denoising.

There are several denoising schemes available. The Stein's thresholding is a compromise between hard thresholding and soft thresholding schemes to be both continuous and unbiased for the large coefficients,

$$\gamma = (1 - t\sigma/|\hat{\alpha}(x)|^2)_+, \tag{1}$$

where γ is the constant to weigh the received value, $\hat{\alpha}(x)$, to estimate the true value, $\alpha(x)$. t is a preset parameter to define the radius of the zero-out region, and σ is standard deviation to normalize this zero-out region. $()_+$ is the unit step function.

With full set of coefficients, the reconstruction based on contourlets shows "scratches" due to the misrepresentation of the contourlet in that region. The reconstruction based on wavelets shows missing “dots” [4], where the shapes of the artifacts from transmission errors are consistent with the shapes of “strokes” used in contourlets and wavelets respectively. Stein’s thresholding effectively remedies the transmission noise for both compression techniques.

B. Face Recognition in Coefficient Domain

After complete image denoising and recovery, a direct face recognition algorithm can be implemented. However, if the resources of the network do not allow full transmission of all the coefficients, the lower band coefficients represent a scaled down version of the face image for a coarse matching as screening, which preserves energy, saves bandwidth and decreases the transmission delay. Meanwhile, face recognition in coefficient domain eliminates the recovering step, which saves calculation and transmission resources. The contourlet transform of a face image is shown in Fig. 2. It can be observed that the lower band coefficients constitute a shrunk version of the original face image. If the recognition result from this coarse image pulls an alarm, a request is sent to the source node to re-send the detailing coefficients. With prioritization of the data, the network resources can be optimally allocated to make sure that the important data are transmitted with little packet loss and small bit error rate [26].

Meanwhile, the contourlet transform is a unique transform to derive the intrinsic features of the face images for recognition. The classification based on contourlet transform is performed in exactly the same way as on the original image pixels, with the only difference being that the data matrix is not composed of pixel values; instead, the data matrix is composed of contourlet coefficients. If the coefficients are columnized in the data matrix, then the lower band coefficients are located at the top, the middle level coefficients fill in the column vector consequently, and the highest level coefficients are located at the bottom. When the transmission is constrained, only the part from the top needs to be transmitted. There is flexibility on the number of coefficients that need to be transmitted.

In data transmission, the lower band coefficients are transmitted with high fidelity, because they are the most important in recognition and reconstruction of the face image. The data are transmitted in packets. The data packet may get lost before it reaches the destination, and the data in a delivered packet may contain errors. An adaptive routing scheme[27], based on swarm intelligence and Bayesian network, trades off between the wireless network resources and transmission accuracy to allocate more resources to high prioritized data. The final weighted accuracy of such a transmission scheme is optimized [28] even under attacks or jamming.

IV. SIMULATIONS

At the first step, denoising by contourlet transform and wavelet transform is compared. Daubechies 4 wavelet is selected for its excellent ability to approximate curvature structure. The expansion level is 2. The contourlet transform is implemented by following Do, et al.’s variations[2] to obtain robustness. The denoising performance of both compression techniques is comparable: Contourlets achieves MSE at 25.33, and wavelets at 32.52.

At the second step, face recognition is implemented. The first face recognition experiment is carried out on ORL database, with 10 face images for each of the 40 subjects. ORL database is relatively small, but it contains a great amount of pose variation and some expression variation, thus it’s suitable to test-run an algorithm. The goal of a wireless face recognition system design is to accomplish the high accuracy recognition of a wired system. It’s promising that the 1st-ranking detection rate by the contourlet transform in the wireless system on ORL database is the same as the wired system at 94%.

Further experiment is conducted on FERET database[29], which consists of images from 1196 individuals under various conditions and at various time. FERET is much bigger than ORL, and it is utilized to test the communication properties of the wireless face recognition system based on contourlet transform by cross validation. The average performance is reported in Fig. 3 and Fig. 4, which illustrate the correct acceptance rate on unseen images from users, and the correct rejection rate on images from imposters, respectively.

It’s very interesting that the surface is not slanting uniformly from the left-upper corner (with small error rate) to the right-lower corner (with big error rate); instead, there’s a big flat region in recognition rate, which shows that the performance does not degrade linearly. The performance drops drastically only when the error rate exceeds some threshold.

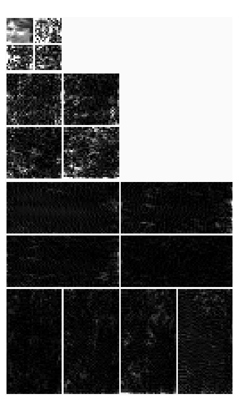

Fig. 2. Contourlet coefficients of a face image

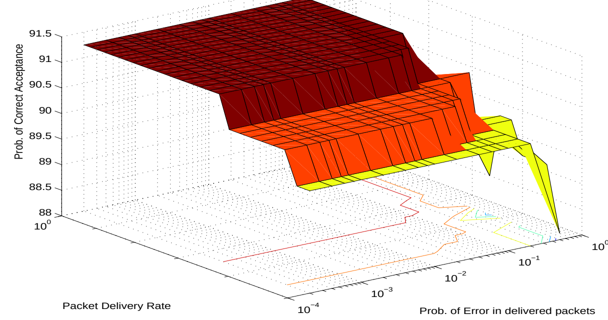

Fig. 3. Correct acceptance rate under various packet delivery rate and probability of error in delivered packets

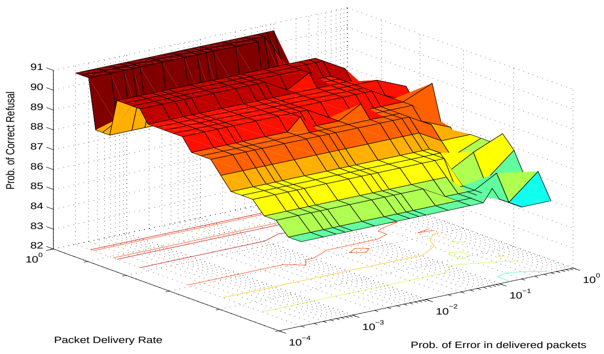

Fig. 4. Correct refusal rate under various packet delivery rate and probability of error in delivered packets

V. CONCLUSIONS

Contourlet transform not only compresses face images, but also serves as feature extractors for face recognition. In a constrained network, only a part of the coefficients need to be transmitted, and the transmitted coefficients constitute the data matrix for subspace based modular processing with fusion. The recognition in coefficient domain assumes a flat region in performance degradation when the data packet delivery rate and the bit error rate of delivered packets increase linearly. This phenomenon shows that the contourlet transform based wireless face recognition system tolerates the transmission error up to a certain level. Within this region, no data need to be resent, which saves wireless network resources and minimizes the transmission delay.

In a wireless transmission system, error resilient entropy coding strategies in combination with FEC (Forward error correction) can be expected to improve the transmission accuracy. There is the tradeoff between the extra bits for correction and the improvement of transmission accuracy. For fair comparison, only bare data, either pixels or coefficients, are compared in this paper. In the future, more delicate error coding schemes can be implemented to identify what kind of data can achieve bigger improvement in accuracy.

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