

Ear and Foot Biometrics Best for Identification

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Abstract: Now a day the person identification is most secure application used in many purpose such as attendance, registration, verification etc. Identification is based on biometrics, like face, ear, iris, fingerprint, signature and keystroke. Many researchers have done the work on different biometrics traits and found out the results using different parameters. In This paper we work on two modalities ear and foot applied eigen image classifier for ear and modified sequential harr transforms classifier for foot. The result of individuals' biometrics is calculated and after that we apply the fusion strategy at match score level. We used sum rule method for fusion to combine the biometrics and calculate the result.

Our paper displayed the result of ear and foot biometric modalities in terms of FAR, FRR and Wight score of individuals, normalized score, combined weight of modalities ear and foot and at last combined matching score of ear and foot. All the results are calculated on self created database of 100 parsons.

Keywords: Multimodal biometrics, Eigen image, modified sequential harr transform, Euclidian distance.

1. INTRODUCTION

Biometrics has become a common system used in various applications such as attendance recording, traffic and toll monitoring; identification of a person etc. The biometrics provides great solution to security technologies. The need for a system being able to recognize people for various purposes is increasing widely. Ross et al. (2003), Biometrics deals with automatic recognition of a person using distinguishing traits which are also known as biometric modalities. A more expansive definition of biometrics is "any automatically measurable, robust and distinctive physical characteristic or personal trait that can be used to identify an individual or verify the claimed identity of an individual" [1] Jain et al. (2004) the term "multimodal" is used to combine two or more different biometric sources of a person like face, ear, iris and foot sensed by different sensors. Multiple sources of biometric information are combined for overcoming some of the limitations mentioned in unimodal biometric system of [2] Multimodal biometrics system involves various levels of fusion, namely, sensor level, feature level, matching score level, decision level and rank level. At Sensor level: The raw data acquired from multiple sensors can be processed and combined to generate new data from which features can be extracted, At Feature level: The feature sets extracted from multiple data sources can be combined to create a new feature set to represent the individual, At Match Score level: Multiple classifiers result scores are combined to generate a single scalar score and At Decision level: When the fusion is at decision level then each matcher outputs are combined to accept or reject in a verification system. Section 2 describes related research in this field. Section 3 gives description of Identification process. Section 4 Explain the method which is applied to the modalities. Section 5 Show Experimental results and conclusion has been discussed.

2. RELATED RESEARCH

Biometrics is the science of identify humans using biological characteristics. Here, the study is based on biometrics methods. Jain et al. (2005) reported that the biometrics is becoming more commonly used in several devices in many places including computer rooms, research labs, airports, blood banks, ATMs and military installations. Researchers have investigated different biometric identifiers based on several factors including application scenario, associated cost and availability of the identifiers. Each biometric trait has its advantages and disadvantages and no single trait is expected to effectively meet all the requirements of all applications.

Ear is a relatively new class of biometrics used for person authentication. Iannarelli et al. (1989) used manual techniques to identify ear images. Over 10,000 samples of ears were studied to prove the distinctiveness of ears. However, the potential for using the ear's appearance as a means of personal identification was recognized. Victor et al. (2002) used PCA and FERET evaluation protocol for ear identification. Burge et al. (1998) introduced geometric algorithm utilizing neighbourhood graph and voronoi detected edges of diagram of ears' curve segments for automated ear recognition. Hurley et al. (2005) applied force field transform to ear images in order to find energy lines, wells and channels. Each image is represented by a compact characteristic vector, which is remarkably invariant to initialization, scale, rotation and noise. The experiment displayed the robustness of the technique to extract the 2D ear.

Yan and Bower (2005) compared PCA and ICP methods on 2D and 3D ear images and introduced a fast method based on ICP for 3D shape images. High recognition rate was obtained for 3D ear shapes. But 3D image acquisition required more time so 2D images are preferred for real-time purposes. Feng et al. (2000) computed Eigen faces from a midrange wavelet sub-band. The method was based on wavelet sub-band using PCA for human face recognition. A mid-range frequency sub-band is selected for PCA representation. Chang et al. (2003) developed an ear recognition system using Eigen ear method and compare with Eigen face method. The Eigen face and Eigen ear were combined to evaluate the performance of the system. Bhanu et al. (2003) presented a 3D ear recognition method using a new local surface descriptor. The similarity of two ears was determined by three factors namely the number of similar local surface descriptors in ears, geometric constraint, and the match quality.

Very limited literature is available on footprint recognition system. Nakajima et al. (2000) proposed a technique for the footprint based recognition. Footprints are standardized, together in direction and in point for sturdiness image-matching between the input pair of footprints and the pair of recorded footprints. The Euclidean distance between the geometric information of the input footprint is used proceeding to the normalization. The pressure distribution of the footprint was measured with a pressure-sensing mat. Jung et al. (2003) proposed methods which are based on human gait, stable, relatively continuing walking data are the crucial conditions for person recognition. In future, these methods are very challenging to accomplish with countless change of walking velocity which may be generated often during real walking. In this literature, they recommend a technique which uses just single-step walking records from mat-type pressure sensor.

Wang et al. (2004) proposed an alternative system grounded on gait investigation. The dissemination of footprint substantial pressure surface reproduces the performance characteristics and the physiological characteristics of the humanoid figure. Consequently, footprint substantial pressure surface pick-up and depiction is the establishment of footprint biological feature identification. Kuragano et al. (2005) suggested a novel approach based on gait and footprint analysis. Health care providers in Japan assess the recovery status of patients by detecting a variation in the patient's style of walking. In the first phase of psychoanalysis, the manner of walking is uneven. By way of rehabilitation progresses, the mode of walking of the patient turn into stable state. The techniques of binarization of a foot print image, noise-reduction, and damage and stretching to smoothening of the edge of the binary image to discover the edge of the footprint image are defined. Wild et al. (2008) published for single-sensor hand and footprint-based multimodal biometric recognition by He has developed a system for contemporary humanity, and as it is assumed that no complete biometric modality suitable for all the applications has been established. The novel modality provisions offers underneath accuracy.

3. IDENTIFICATION PROCESS

We worked on two level of fusion strategy, matching score level and decision level. For this we used ear and foot biometric traits and eigenimage approach for ear and modified sequential harr transform approach for foot to calculating matching score. At decision level we showed that the image which is used as biometric accept/reject.

At matching score level, we calculate False accept rate (FAR), False reject rate(FRR) and Equal Error Rate (EER).

Weight of individual modalities W_i is calculated as

$$W_i = \frac{1}{EER_i}$$

We used Min-Max normalization technique to calculate normalized score of each trait.

$$y = \frac{x - \min(S_x)}{\max(S_x) - \min(S_x)}$$

After Normalization we found similar match score of all biometric traits. Now we calculate weight of particular trait of all biometric traits i.e., i th particular trait, weight W_i is calculated as

$$W_i = \frac{\frac{1}{EER_i}}{\sum_{j=1}^n \frac{1}{EER_j}}$$

Where EER_j is the equal error rate for j th trait and n represents the number of traits participating in fusion.

We used in the sum rule based fusion. After we found normalized score we calculated individual traits weight. Then we computed the fused score S as

$$S = \sum_{j=1}^n (W_j S_j)$$

where S_j is the match score and W_j is the weight of j th trait. The range of fused score S calculated by this technique is also $[0,1]$ because $\sum W_j = 1$.

4. PROPOSED METHOD

we present the methodology for the proposed multimodal biometric system based on matching level fusion, and decision level fusion utilizing ear and foot biometric information.

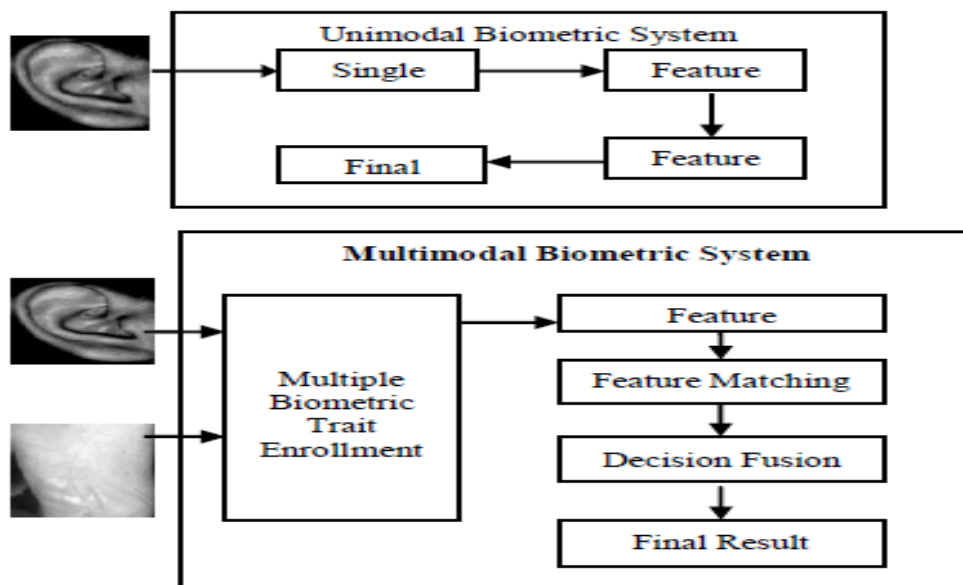


Fig. 1: Unimodal biometric, Multimodal biometric recognition process Eigenimage

Ear is a relatively new class of biometrics much like the face is a visible part of the human body that can be used for a non invasive biometric technique. Humans most likely will have to keep their ears uncovered to be able to hear. Ear is a stable biometrics and does not vary with age. “Eigenimage”, is also known as Principal Component Analysis. Darwish et al.(2009) described Eigenimage is one of the most known global Ear recognition algorithm. The main idea is to decorrelate data in order to highlight differences and similarities by finding the principal directions (i.e., the eigenvectors) of the covariance matrix of a multidimensional data. For our experiments, first we initialize the ear recognition process by using the training set, i.e. the images of ear. The side face images have been acquired using high quality camera in the same lighting condition. The ear part is cropped from the side face image. The colored image is then converted to grayscale image.

In eigenimage algorithm From a theoretical point of our view, a ear image can be seen as a vector is a huge dimensional space, concatenating the columns. Our research based on normalized ear images that we preprocessed. Then we calculate eigen vectors and eigenvalues on the covariance matrix of those images. Wang, et al.(2003). Defined the highest eigenvectors are kept. Finally, the known images are projected onto the image space, and their weights are stored.



Fig. 2: Ear images.

Modified Sequential Haar Wavelet Transform Technique

Foot image features are generally extracted by transform-based method like Discrete Cosine Transform and Fourier Transform. According to Wenxin et al.(2002) in Fourier Transform floating-valued signals involve into integer-valued signals gives less accuracy, and Jing et al.(2004) in Discrete Cosine Transform some points are missed leading to incorrect inference. Qian,et al.(2002) introduced another Transform method is wavelet Transform which is used to take out the features of the foot image Sequential modified Haar Wavelet is planned to find the Modified Haar Energy (MHE) feature. The Haar wavelet coefficients are represented using decimal numbers. Sequential modified Haar transform is applied to the resized footprint image to obtain Modified Haar Energy (MHE) feature. The sequential modified Haar wavelet can map integer-valued signals onto integer-valued signals abandoning the property of perfect reconstruction. The MHE feature is compared with the feature vectors stored in database using Euclidean Distance. The accuracy of the MHE feature and Haar energy feature under different decomposition levels and combinations are compared.



Fig. 3: Foot images.

5. EXPERIMENTAL OUTCOMES

A database are created that consists of 100 person’s images for ear and foot using high quality camera and sufficient light. An ear image of size $p \times q$ pixels is represented by a vector in $p.q$ dimensional space by eigen images and Sequential modified Haar transform is applied to the resized footprint image to get Modified Haar Energy (MHE) feature. every image of the detail coefficients is further divided into 4×4 blocks to calculated min MHE of foot images. Figure 4 to 9 shows the experimental results using matlab software apply on ear and foot modalities training set and test set are prepared for each modalites. Each classifier has its own representation which is describe in figures.

Figure 4 to Figure 7 present results for ear images

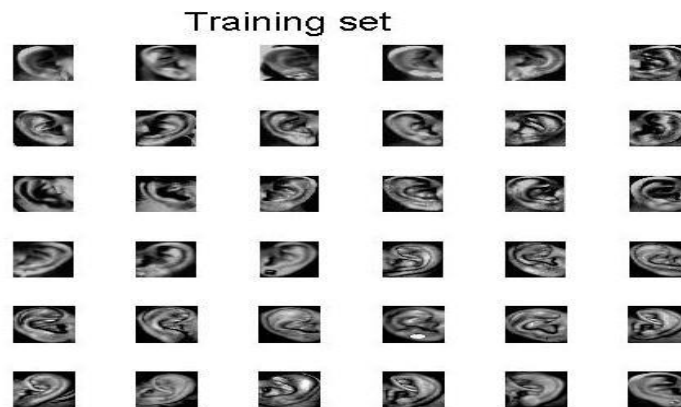


Fig. 4: Training set of ear images.



Fig. 5: Normalized images of ear images.

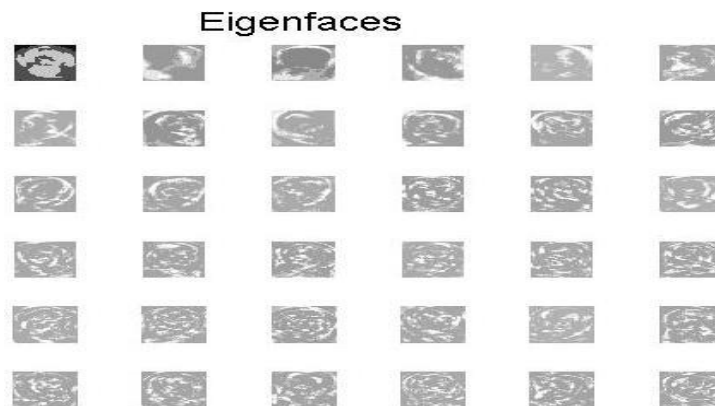


Fig. 6: Eigen ear.

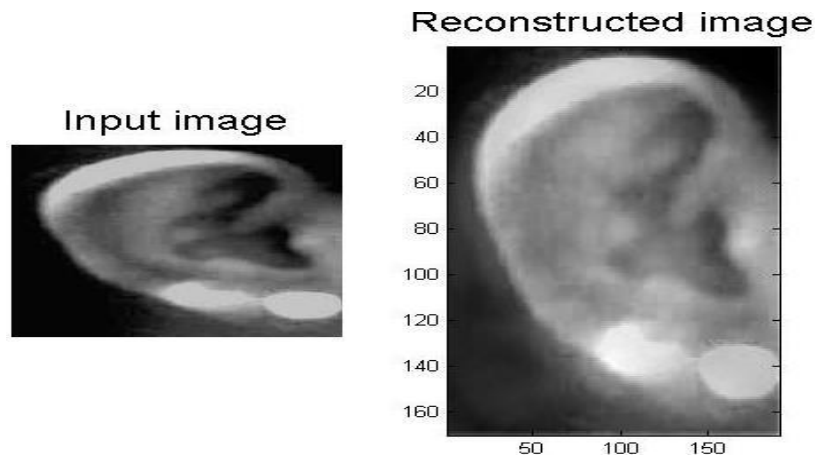


Fig. 7: Input image and reconstructed image.

Figure 8 to Figure 9 present results for foot images

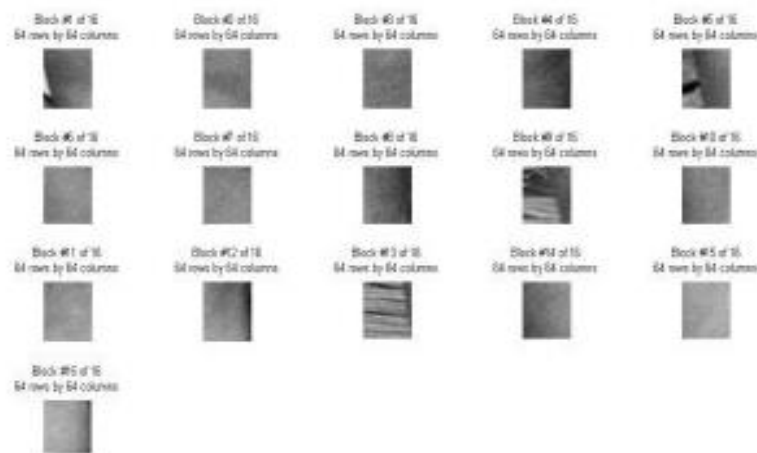


Fig: 8 foot image in 4x4 blocks

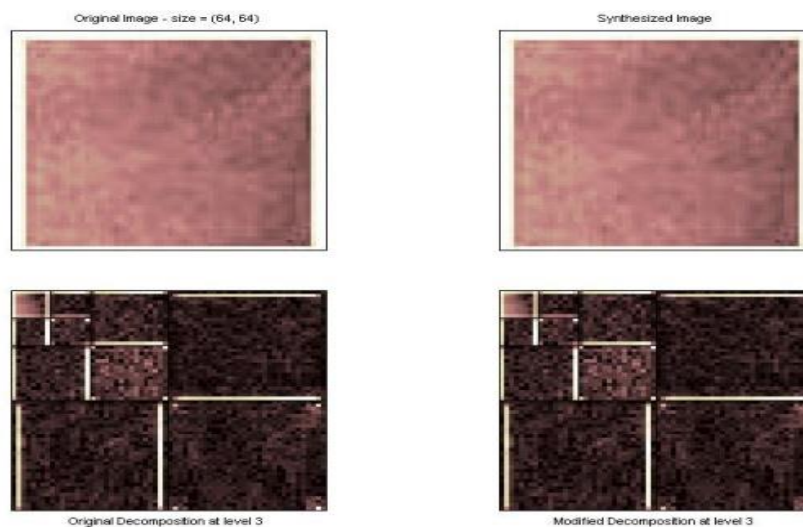


Fig. 9: (a) Original image, (b) Synthesized image, (c) Original Decomposition at level 3, (d) Modified Decomposition at level 3

6. RESULTS

We use ear and foot modalities on self created database of 100 person's using high quality camera and sufficient light. All training and testing data convert into gray scale, cropped and resize. Matlab software is used to calculate results. Shown in previous The minimum-distance is calculated by Euclidian distance for faces, ears and foot shown in Table 1.

Table 1 : Euclidian distance for Ears and Foot

Ears	Minimum Euclidian distance for ears	Foot Image	Minimum Euclidian distance for foot
Pe1	1.5343E+04	Pfo1	6.7719E+003
Pe2	1.5307E+04	Pfo2	6.6783E+003
Pe3	1.5274E+04	Pfo3	7.0295 E+003
Pe4	1.5265E+04	Pfo4	7.0445 E+003
Pe5	1.5257E+04	Pfo5	6.6188 E+003
Pe6	1.5252E+04	Pfo6	6.9126 E+003
Pe7	1.5244E+04	Pfo7	6.8937 E+003
Pe8	1.5247E+04	Pfo8	6.8419 E+003
Pe9	1.5247E+04	Pfo9	6.7982 E+003
Pe10	1.5254E+04	Pfo10	6.7911 E+003

Face, ear and foot algorithms are tested individually and the results of individual modalities are calculated in term of weight, EER, FAR, FRR shown in Table 2:

Table 2: Individual Trait Ear and Foot

Traits	Weight	EER	FAR	FRR
Ear	0.96	1.031	1.08	0.98
Foot	0.91	1.099	1.25	0.94

At fusion stage we apply min-max normalizations for similarity score because all recognition scores are dissimilar. and calculate weights for fusion .There are 3 possible fusion of two traits Table 3 shows the weights assigned to different traits in all possible fusion . Finally we calculate the matching score of all possible combinations of traits shows in table 4. The sing + denotes the fusion highest matching score 0.13 calculated for ear and foot modalities

Table 3: Calculate weight for each traits in all possible fusion of two traits

Traits	Ear	Foot
Ear	0.51	-
Foot	-	0.49
Ear+ Foot	0.51	0.48

Table 4: Calculate matching score of all possible traits

Traits	Ear +Foot
Score	0.13

7. CONCLUSIONS

Recently, several contributions have been made in the field of biometrics and investigations have been carried out in the domain of multi-modal biometrics. When multiple biometric traits combine using different fusion methods to achieved optimal result .Paper shows, Eigen imageand modified sequential harr transform based multimodal biometrics has been presented using Ears and Foot modalities for self created databases. Multimodal biometrics Ear and Foot has resulted 0.13 improved performances in terms of recognition score.

REFERENCES

- [1] R. Arun, Jain Anil, et al. Multimodal Biometrics: An Overview[C]. Proceedings of 12th European Processing Conference, 2004.1221-1224(Vienna, Austria)
- [2] A.Ross, A.K.Jain, et al. Information fusion in biometrics. Pattern Recognition Letters, 2003, 24(13):2115 –2125.
- [3] M. Turk, A. Pentland et al. Eigenfaces for recognition[J]. Journal of Cognitive Science. 1991. 3(1):71-86.
- [4] D.R. Kisku, J. K. Singh, M. Tistarelli,et al. Multisensor biometric evidence fusion for person authentication using wavelet decomposition and monotonic decreasing graph[C]. Proceedings of 7th International Conference on advances in Pattern Recognition (ICAPR)2009:205-208 (Kolkata, India)
- [5] W. Zhao, R. Chellappa, A. Rosenfeld, P. J. Phillips,et al. Face Recognition[J]. An ACM Computing Surveys, 2003, 35(4):399-458.
- [6] X. Y. Jing, Y.F. Yao, J.Y. Yang, M. Li, D. Zhang et al. Face and palmprint pixel level fusion and kernel DCVRBF classifier for small sample biometric recognition[J]. Pattern Recognition, 2007, 40 (3): 3209-3224.
- [7] Cappelli, R., Maio. D, Maltoni et al. Combining fingerprint classifiers. In First Internet. Workshop on Multiple Classifier Systems, 2000,35(1) : 351–361
- [8] L. Hong and A. K. Jain et al. Integrating faces and fingerprints for personal identification, IEEE Trans. Pattern Anal. Mach. Intell., 1998: 20(12) : 1295–1307.
- [9] R. Frischholz and U. Dieckmann et al. Biold: A multimodal biometric identification system,” Computer, 2000,33(2) : 64–68
- [10] J. Fierrez-Aguilar, J. Ortega-Garcia, D. Garcia-Romero, and J. Gonzalez-Rodriguez et al. A comparative evaluation of fusion strategies for multimodal biometric verification, in Proc. 4th Int. Conf. Audio- Video-Based Biometric Person Authentication,2003, 2688: 830–837.
- [11] A.Ross, R.Govindarajan et al. Feature level fusion using hand and face biometrics[C].Proceedings of SPIE Conference on Biometric Technology for Human Identification, 2004, 5779:196 –204(Orlando ,USA)
- [12] T. Wang, T. Tan, and A. K. Jain et al. Combining face and iris biometricsfor identity verification, in Proc. 4th Int. Conf. Audio- Video-Based Biometric Person Authentication, 2003 LNCS 2688: 805–813.
- [13] K. A. Toh, X. D. Jiang, and W. Y. Yau et al. Exploiting global and local decisions for multi-modal biometrics verification, IEEE Trans. Signal Process., 2004,52(10) : 3059–3072.
- [14] R. Snelick, U. Uludag, A. Mink, et al. Large scale evaluation of multimodal biometric authentication using state-of-the-art systems, IEEE Trans. Pattern Anal. Mach. Intell., 2005,27(3): 450–455.
- [15] K. Jain, K. Nandakumar, and A. Ross, “Score normalization in multimodal biometric systems,” Pattern Recognit., 2005. 38(12): 2270–2285.
- [16] W. Kong, D. Zhang et al. Accurate iris segmentation based on novel reflection and eyelash detection model. Proceedings of 2001International Symposium on Intelligent Multimedia, Video and Speech Processing, 2001,(Hong Kong)

- [17] D.R. Kisku, J. K. Singh, M. Tistarelli, et al. Multisensor biometric evidence fusion for person authentication using wavelet decomposition and monotonic decreasing graph[C]. Proceedings of 7th International Conference on advances in Pattern Recognition (ICAPR-2009):205-208 (Kolkata, India)
- [18] G.R. Sinha, Kavita Thakur, et al. Modified PCA based Noise reduction of CFA images[J]. Journal of Science, Technology & Management, 2010,1 (2):60-67.
- [19] Snehlata, G.R.Sinha et al. PCA based Multimodal Biometrics using Ear and Face Modalities[J] International Journal of Information Technology and Computer Science(IJITCS).2014,6(5), :43-49.
- [20] Snehlata, G.R.Sinha et al. Multimodal Biometrics using Face, Ear and Iris Modalities[c] International Journal of Computer Applications Recent Advances in Information Technology NCRAIT (2),2014:9-15.