

t-SNE based Multi-mode Medical Image Fusion Algorithm

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Abstract— Based on the research on the t-Distributed Stochastic Neighbor Embedding (t-SNE), t-SNE algorithm is applied to the medical image fusion. t-SNE is considered an excellent algorithm for the data visualization. The mapping from high dimensional data with low dimensional manifolds is adroitly used to perform image fusion. First we apply the K-L transform to multi-mode the images, then t-SNE carries out the fusion. The results indicate the multitudinous benefits such as faster execution speed, greater information entropy and broad dynamic range. Applications span, but not limited to, MRI scans, CT scans

Keywords— Image fusion, t-SNE, Pyramid fusion, DWT, Gradient, Entropy.

I. INTRODUCTION

IN order to cater medical issues reflected through images of human body, organs, and cells the patient is often imaged by many kind of patterns or a single pattern. To improve the efficacy of the medical practitioners in arriving at an unbiased and objective decision in a short span of time, more integrated information can be obtained by using the result of multiple image so that the clinical diagnosis and treatment, more comprehensive and precise [1][2].

There exist many open questions such as computation speed of image fusion, minimization of information loss, centralizing the dynamic range of fusion and so on. This paper is mainly concerned with multi-mode medical image fusion method based on the t-SNE algorithm. Historically, t-SNE has been used to visualize the data. It has proven to be quite effective in mapping high dimensional data to low dimensional manifolds, especially with images. [3] For the first time, we demonstrate that it can be used for fusion of medical images. As t-SNE imports the shapes to the lower dimensions, it means one simply has to deal with fewer amounts of data. This significantly improves the speed of the execution. Due to efficacy of t-SNE, especially the utilized random walk mechanism, the information entropy increases.

The paper is organized as follows. Section II presents the highlights of the t-SNE algorithm, including its cost function. Section III describes the in-depth methodology of the algorithm. Section IV deals with the experimental analysis and

the clearly indicating the significance of the proposed method.

II. THE T-SNE ALGORITHM

A data point in a t-SNE algorithm is a point x_i in the original data space R^D . A map point is a point y_i in the map space R^2/R^3 . Every map point represents one of the original data points t-SNE is a visualization algorithm that choose positions of the map points in R^2/R^3 .

We restricted our work only to R^2 space. Ideally, if exemplar is in R^3 , then it is a sensible choice to use R^3 mapping, since one can make out 1-to-1 mapping. Our data (each image) is in R^2 , so did not experiment with R^3 . Even if R^3 mapping is used the results should remain the same, at least theoretically.

But pragmatically, implementation wise, data gets crunched into linear representation, and if there is a mismatch in spaces, i.e. non linear mapping, results might become haphazard.

A. t-SNE PROCEDURE:

Following is the step by step procedure of the t-SNE algorithm [4].

- 1) Compute an $N \times N$ similarity matrix in the original R^D space
- 2) Define an $N \times N$ similarity matrix the low-dimensional embedding space which acts as a learn objective
- 3) Define cost function - Kullback-Leibler divergence between the two probability distributions
- 4) Learn low-dimensional embedding.

The result of the t-SNE focuses on accurately modelling small pairwise distances, i.e., on preserving the local data structure in the R^2/R^3 , in our case; it is R^2 .

The Similarity of data points x_i in data space R^D is given by

$$p_{j|i} = \frac{\exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma_i^2}\right)}{\sum_{k \neq m} \exp\left(-\frac{\|x_k - x_m\|^2}{2\sigma_i^2}\right)} \quad (1)$$

Where $p_{j|i}$ measures how close x_j is from x_i , considering Gaussian distribution around x_i with a given variance of σ_i^2

The main advantage of symmetry is simplifying the gradient, i.e. the learning phase:

$$p_{ij} = \frac{p_{i|j} + p_{j|i}}{2N} \quad (2)$$

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Here, p_{ij} is a similarity metric and N is the number of perplexity, i.e. effective number of neighbors. Also note that p_{ij} is symmetric.

Student t -distribution with one degree of freedom (same as Cauchy distribution) [5] is given by:

$$q_{ij} = \frac{(1 + \|y_i - y_j\|^2)^{-1}}{\sum_{k \neq m} (1 + \|y_k - y_m\|^2)^{-1}} \quad (3)$$

p_{ij} in equation (2) is fixed, whereas q_{ij} in equation (3) is flexible. We want p_{ij} and q_{ij} to be as close as possible. A few facts about (3), we set q_{ij} to 0, as we are interested in pairwise similarities. The distribution is still closely related to Gaussian [6], but it is computationally convenient since no exponent is involved.

$$C = \sum_i KL(P_i \| Q_i) = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}} \quad (4)$$

A few facts about KL divergence [7]

- It is not a distance, since it is asymmetric
- large p_{ij} modelled by small $q_{ij} \rightarrow$ large penalty
- small p_{ij} modelled by large $q_{ij} \rightarrow$ small penalty
- KL divergence meaning: cross-entropy

III. REALIZATION OF THE T-SNE FUSION ALGORITHM

The concrete steps of image fusion based on t -SNE can be described as follows.

- 1) Read in CT and MRI images whose sizes are 64×64 , annotated as m_1 and m_2 respectively.
- 2) Define 64×64 similarity matrix and apply Kullback-Leibler transform [7], which is already mentioned in the equation (4)
- 3) The output of step 2), i.e. two 1×2 matrices a and b , as we restricted the dimensionality reduction to R^2 , is applied to the original images to obtain the ratios of the energy.

The ratios are found out by simply multiplying the 1×2 matrices with the t -SNE output matrices of size 2×1 each. Each ratio is then represented as the first component of the t -SNE output matrix, i.e. a divided by the row sum of the similarity matrix. Hence it becomes $a/(a+b)$. Similarly, second ratio $b/(a+b)$ is found out.

4) Image fusion is carried out according to $a/(a+b)m_1$ and $b/(a+b)m_2$. $a/(a+b)$ and $b/(a+b)$ are the ratios of the t -SNE information and the energy.

5) Carry on K-L inverse transformation, namely obtain the fusion image.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The purpose of a CT scan is to have a closer look at the soft tissues and organs in the patient's body [8]. It will also help diagnose an infection, and surgeons may also use CT scans to identify masses and tumors, or to reach the right area during a biopsy. CT scans also help with the study of blood vessels. MRI has a wide range of applications in medical diagnosis and over 25,000 scanners are estimated to be in use worldwide [9]

MRI affects diagnosis and treatment in many specialties although the effect on improved health outcomes is uncertain [10]. Since MRI does not use any ionizing radiation, its use is generally favored in preference to CT when either modality could yield the same information [11]. (In certain cases, MRI is not preferred as it can be more expensive, time-consuming, claustrophobia-exacerbating).

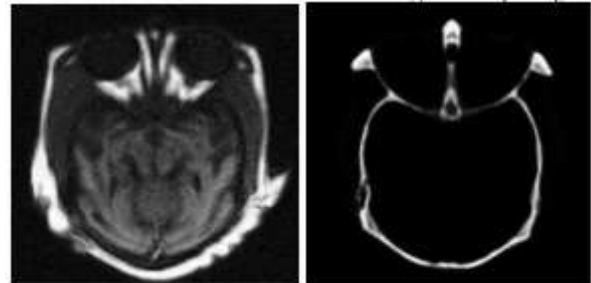


Fig.(a) MRI Sample Image

Fig.(b) CT Sample Image

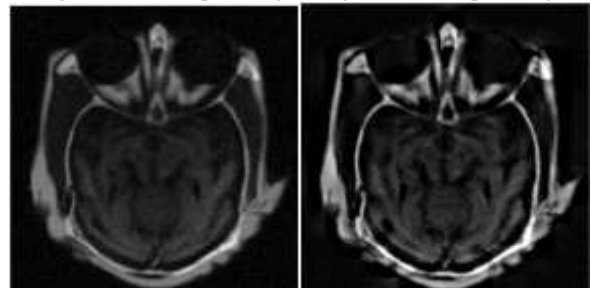


Fig.(c) Fused Image

Fig.(d) DWT fusion

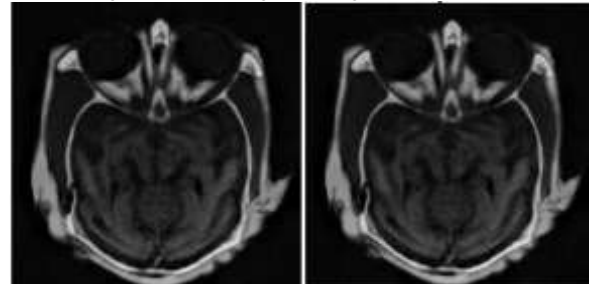


Fig.(e) Gradient Pyramid fusion Fig.(f) FSD Pyramid fusion

Taking the method based on the ratio of t -SNE information and energy, we may obtain the fusion image shown below.

For comparing our efficiency, we implemented multiple other algorithms performing the same task. The output of DWT [13], Gradient Pyramid [14], and FSD Pyramid [15] are shown in the fig.(d), fig.(e) and fig.(f).

From fig.(c) and fig.(d), fig.(e) and fig.(f), we may conclude that the obtained fusion image with the method based on the ratio of t -SNE information and energy, the outline and the muscular tissue fuse quite perfectly. It does not have the double image and the integral color is consistent, so it can reflect the important information from the perspective of a diagnosis. Double image is a simple phenomenon caused by fusing multiple images where one can clearly visually experience both of the images at the same time.

Objectively, we use information entropy h , average gradient g and discrepancy d as the appraisal parameter of fusion image and the result is shown in table-1. It can be clearly seen that the newly proposed method outperforms all the existing

methods on all the three parameters. The second closest match is the fusion based on the principle component analysis [17].

TABLE I
GRADIENT AND ENTROPY COMPARISON

	Average gradient $t(g)$	Information entropy (h)	Discrepancy (d)
CT image	3.0590	0.0012	7.3040
MRI image	5.7124	0.0016	4.6479
the fusion image based on t-SNE	19.7052	0.059	1.6104
DWT fusion image	6.8963	0.0315	5.1737
Gradient Pyramid fusion image	5.3832	2.4414e-004	5.3250
FSD Pyramid fusion image	5.4275	2.4414e-004	4.9766
The fusion based on principle component analysis	17.7268	0.0492	2.2192
Basic PCA fusion image	5.4267	2.4414e-004	4.0269

Through comparing the value of average gradient, the average gradient of fusion image based on the ratio of t-SNE information and energy is much larger than that of the original CT image fig.(a) and MRI image fig. (b). This illustrate that the detail information of fusion image is rich, and the textural property is obvious. At the same time, the information entropy absolute value of fusion image is far bigger than the original CT image and MRI image. This explains that the quantity of information reflected from the fusion image is improved greatly. The morerequirement of medical information is reflected at the same time. The fusion effect is perfect.

V. CONCLUSION

The K-L transformation of multi-mode image is carried on, through solving the probabilistic t-SNE dimensionality reduction, carried on the image fusion in the new space. The result indicated that this algorithm has many characteristics, such as the fast execution, great information entropy and broad dynamic range. In clinical and the industrial production, the size is often big, which sharply increases the covariance dimension and computation load, bringing the challenges for speed to fuse. So we still discuss on how to simplify computation and extract the principal components information. DWT fusion

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