

Multi-Scale Recognition of Objects Approach based on Inherent Redundancy Information Entropy Equalization.

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ABSTRACT

Development of new imaging sensors arise the need for image processing techniques that can effectively fuse images from different sensors into a single coherent composition for interpretation. In order to make use of inherent redundancy and extended coverage of multiple sensors, we propose a multiscale approach for pixel level image fusion. The ultimate goal is to reduce human/machine error in detection and recognition of objects. The simulation results show that the proposed algorithm has increased the rate of object detection.

INTRODUCTION

Wide variety of pixel-level image fusion algorithms has been developed. These techniques may be classified into linear superposition, logical filter [1], mathematical morphology [2], image algebra [3], artificial neural network [4], and simulated annealing [5] methods. Each of these algorithms focuses on the fact that the fused image reveals new information concerning features that cannot be perceived in individual sensor images. However, some useful information has been discarded since each fusion scheme tends to emphasize different attributes of the image. Traditional methods provide a detailed review of these techniques. Inspired by the fact that the human visual system processes and analyzes image information at different scales, researchers recently proposed a multiscale based fusion. Proposed method extends the concept to apply entropy to measure the joint histogram as dissimilarity metric between images. Inspired by this previous work, and looking to address their limitation in often difficult imagery, we introduce in this paper a novel generalized information theoretic measure, namely the Jensen divergence and defined in terms of entropy [6]. Jensen divergence is defined as a similarity measurement among any finite number of weighted probability distributions. Shannon mutual information is a special case of the Jensen divergence. This generalization provides us an ability to control the measurement sensitivity of the joint histogram, to ultimately result in better registration accuracy.

METHODS AND MATERIALS

ISAR imagery is induced by target motion, and the target motion in turn causes time-varying spectra of the received signals. Motion compensation has to be applied to obtain a high resolution image. The objective of ISAR image registration is to estimate the target motion during the imaging time. Euclidean transformation with translational parameter, rotational parameter and scaling parameter given two ISAR image frames, the estimates of target motion parameters. Using the Jensen inequality, it is easy to check that the Jensen divergence is non-negative. It is also symmetric and vanishes if and only if the probability distributions are equal, for all dimensional representation of the Jensen divergence for two Bernoulli probability distributions, When the Jensen divergence is exactly the generalized Jensen-Shannon divergence [6]. Unlike other entropy-based divergence measures such as the well-known Kullback divergence, the Jensen divergence has the advantage of being symmetric and generalizable to any finite number of probability distributions, with a possibility of assigning weights to these distributions. The following result, in a sense, clarifies and justifies calling upon the Jensen divergence as a measure of disparity among probability distributions. The Jensen divergence achieves its maximum value when are degenerate distributions. The domain is a convex polytope in which the vertices are degenerate probability distributions. That is, the maximum value of the Jensen divergence occurs at one of the degenerate distributions.

Since the Jensen divergence is a convex function, it achieves its maximum value when the entropy function of the weighted average of degenerate probability distributions, achieves its maximum value as well. Assigning weights, to the degenerate distributions which easily falls out of the Jensen divergence, may be used as a starting point. Without loss of generality, consider the Jensen divergence with equal weights. Since, are degenerate distribution. Let denote a non-increasing ordering of the components of a vector, said to be majorized performance bounds of the Jensen divergence in terms of the error and also of the asymptotic error of the NN classifier are derived. By a classifier we mean a function that classifies a given feature vector to the class. Denote be two random variables taking values respectively. It is well known that the classifier that minimizes the error probability is the result of the classifier with an error L written in discrete form as method that provides an estimate for the error without requiring knowledge of the underlying class distributions is based on the NN classifier which assigns a test pattern to the class of its closest pattern according to some metric. Fig. 1 demonstrates a NN classifier. For sufficiently large, the following result relating the error and the asymptotic error of the NN classifier holds, the following inequality is deduced which is the conditional probability of given for the corresponding pixel pairs. Here the Jensen divergence acts as a similarity measure between images. If the two images are exactly matched, the Since degenerate distributions, the Jensen divergence is maximized for a fixed show two brain images in which the misalignment is a Euclidean rotation.

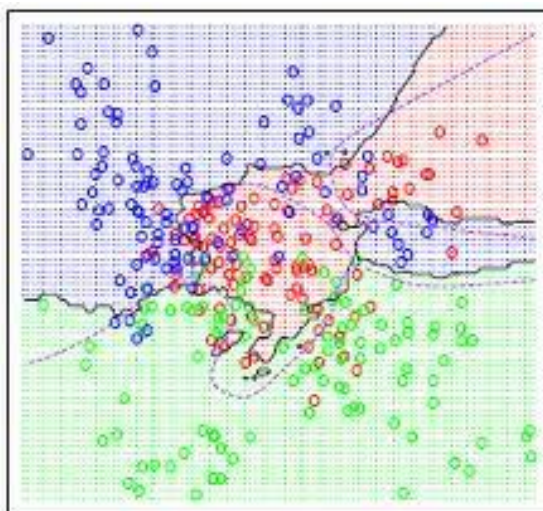


Figure 1: NN classifier categorized 2-dimensional extracted features

RESULTS AND DISCUSSION

The conditional probability distributions are crisp, when the two images are aligned, and dispersed, when they are not matched. It is worth noting that the maximization of the Jensen divergence holds divergence is exactly the Shannon mutilating the mutual information and the Jensen divergence of and uniform weights. The peak at the matching point generated by the divergence is clearly much higher than the peak by the mutual information. It gives the background pixel the largest weight. In the presence of noise, the matching in back-ground is corrupted. Mutual information may fail to identify the registration point. The following proposition establishes the optimality of the uniform weights for image registration in the context of the divergence. After assigning uniform weights to the various distributions in the divergence, a free parameter which is directly related to the measurement sensitivity remains to be selected. In the image registration problem, one desires a sharp and distinguishable peak at the matching point. The sharpness of the divergence can be characterized by the maximal value as well as the width of the peak. The sharpest peak is clearly a Dirac function. The following proposition establishes that the maximal value of the divergence is independent of if the two images are aligned, and yields the sharpest peak. In real world applications, there is a tradeoff between optimality and practicality in choosing. If one can model the misalignment between completely and accurately, would correspond to the best choice since it generates the sharpest peak at the matching point. It is, however, also the least robust selection, as it tends to make all the same as the uniform distribution, if it is not degenerate distribution, then the divergence would be zero for the whole transformation parameter space as in case where the adapted transformation group cannot accurately model the relationship accurate enough. On the other hand, the most robust choice, in spite of also resulting in the least sharp peak. The choice of therefore depends largely on the accuracy of the invoked model and on the specific application as well as the available computational resource. As an example, in Fig. 2 demonstrates the registration results of the two brain images with the choice of different spatial information. In this case, the best choice and would generate a Dirac function with a peak at the matching point. Generating an ISAR image by using stepped frequency waveform can be understood as a process of estimating the target's two-dimensional reflectivity density function from data collected in the frequency space. Suppose a stepped frequency burst consists of pulses in which the transmitted frequency linearly increases from where s the base frequency is the step frequency. Let transmitted

pulse be a pulse of duration T and expressed in within some acceptable tolerance. The proposed compressive model demonstrates that our proposed algorithm is so effective than other old techniques.

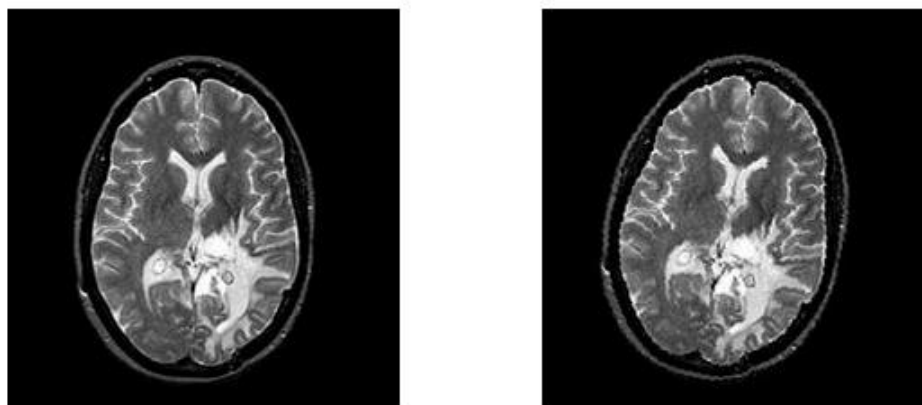


Figure 2: Demonstrates the registration results of the two brain images with the choice of different spatial information

CONCLUSION

In this paper, we Attempt to extend current approaches to signal estimation in a wavelet framework, which have generally relied on the assumption of normally distributed perturbations, we proposed a novel non-linear altering technique, as a pre-processing step for the shapes obtained from an ISAR imaging system. The key idea is to project a noisy shape onto a wavelet domain and to suppress wavelet coefficients by a mask derived from curvature extrema in its scale space representation. For a piecewise smooth signal, it can be shown that filtering by this curvature mask is equivalent to preserving the signal point wise H older exponents at the singular points, and to lifting its smoothness at all the remaining points.

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