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Correlation in Image Fusion using Pearson Correlation Theory

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***Abstract*— we propose a Correlation approach for fusion of images gathered by different wireless sensors on the basis of Mark Pearson's correlation theory. In this paper we present a comparison of previously available and applied correlation approaches. Our method is based on calculating the intensities of the pixels of the image and its gray scale equivalent.**

***Index Terms*-- Pearson theory, Dempster Shafer theory, Correlation, Image fusion**

I. INTRODUCTION

Correlation analyses are one of the most popular quantitative methods of analysing data, yet also one of the mostly frequently misused methods in social and behavioural research. The level of accuracy is dependent on the information gained by the sensors combining data with other sensors that focussing on the same target can enhance the information. Data is not independent the presence of correlation can lead to miscalculation in the fusion. Therefore correlation is to be finding out before fusion and then eliminating it before transmission of the data to the higher level of the fusion architecture.

Correlation is a statistical technique that describes the degree of relationship between two variables .

We apply the Pearson theory of Correlation to the spatial correlation problem. Usually the correlation problem is solved using a Bayesian approach by evaluating the likelihood function for each possible assignment and choosing the maximum likelihood function as the correct assignment. A simulatory comparison is then made between the decisions arrived at using the Dempster Shafer theory and those found using the (traditional) Bayesian approach. The results show (for the cases examined) that the decisions made by both theories are identical. There are several co-relational analysis options when deciding how to analyse ordinal data. Some argued to treat Likert or similar rating scale data, containing five or more Categories, as continuous (Bollen and Barb 1981) and to use Pearson's product-moment correlation coefficient, r (Pearson 1957) to analyse such data. Pearson's r is an appealing choice because it is easy to calculate, interpret, and/or extend to further analyses. We divide the whole process in two stages: first we calculate the correlation coefficient of the original image and then transform the image into its gray scale equivalent and apply the Pearson's correlation theory on it to find the correlation coefficient and then compute the standard deviation between two coefficients, which will be the final result for us.

II. DEMPSTER SHAFER APPROACH

Dempster-Shafer theory is a mathematical theory for combining the evidences obtained from different sources and evaluating the conflict between them. The purpose of aggregating such information is to meaningfully summarize and simplify a corpus of data. The Dempster-Shafer theory is primarily based on the assumption that each of those multiple sources from which results have been obtained is independent of the others. If m1(A) an m2(A) are the results evidences from two independent measurements then the combined result (evidence) is given by:

$$\{m1\ (A) * m2(A)\} / (1-k) \qquad (1)$$

Where, k is the normalization factor which varies from 0 to 1.

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III. BAYESIAN APPROACH

Information fusion based on Bayesian inference offers a formalism to combine evidence according to rules of probability theory the uncertainty is represented in terms of conditional probabilities describing the beliefs and it can assume values in the [0;1] interval, where 0 is the absolute disbelief and 1 is the absolute belief. Bayesian inference is based on the other old Baye's rule which states that:

$$Pr(Y|X)=(Pr(X|Y)Pr(Y))/Pr(X) \qquad (2)$$

Where the posterior probability Pr(Y|X) represents the belief of hypothesis Y given the information X. This probability obtained by multiplying Pr(Y),the prior probability of the hypothesis Y by Pr(X|Y), the probability of receiving x given that y is true, Pr(X) can be treated as a normalizing constant. The main issue regarding the Bayesian inference is that the probability Pr(X) and Pr(X|Y) have to be estimated or guessed beforehand since they are unknown.

IV. COMPARISON STUDY

Five different monte-carlo simulations were run using both approaches to solve the correlation problem. In each run the coordinates of the true positions are taken from independent uniform random variables over the interval [−2, 2]. Then the positions of the objects that the sensors detect are found from the true positions plus errors that are bivariate normal with zero means and variances that are σ12 and σ22, respectively, and are uncorrelated.
Sensor 1 can detect M objects and sensor 2 detects N objects. The first two cases (denoted by A and B) compared measurement sets of equal order (M = 2 and N = 2) while the remaining three cases (denoted by C, D, and E) compared measurement sets of unequal order (M = 2 and N = 3).

TABLE I

COVARIANCE MATRIX ASSUMPTIONS FOR THE DIFFERENT SIMULATIONS.

Case	M	N	σ12	σ22
A	2	2	0.01	0.01
B	2	2	0.01	0.64
C	2	3	0.01	0.01
D	2	3	0.64	0.01
E	2	3	0.01	0.64

Results of the monte-carlo simulation are shown in table 2. The results were identical for both approaches for all runs.

TABLE II

PROBABILITY OF CORRECT CORRELATION BASED ON 500 MONTE-CARLO RUNS.

Case	Bayesian	Dempster Shafer
A	0.998	0.998
B	0.912	0.912
C	0.98	0.98
D	0.702	0.702
E	0.678	0.678

V. PROPOSED METHODS

Understanding developed from the above three methods, let us propose a new approach to correlate the images.
In this approach, the correlation coefficient of original image ro has been formalised using Pearson correlation coefficient and then the image is transformed into its gray-scale equivalent and the correlation coefficient rg is calculated:

$$r = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sqrt{\left(\sum X^2 - \frac{(\sum X)^2}{n}\right)\left(\sum Y^2 - \frac{(\sum Y)^2}{n}\right)}}$$

where x is the intensity of the Ith pixel in image 1, y is the intensity of the Ith pixel in image 2.The correlation coefficient has the value r=1 if the two images are absolutely identical, r=0 if they are completely uncorrelated, and r=-1 if they are completely anti-correlated, for example, if one image is the negative of the other.
The r value indicates whether the object has been altered or moved. Then we calculate the Standard deviation between the original correlation coefficient and the correlation coefficient of the gray-scale image. The result of this standard deviation will be the final correlation coefficient of our approach.

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VI. CONCLUSION

We propose in this paper an approach to analyse and combine the data from different sensors applied in spatial domain, the extraction of features from sensors makes use of the characteristics of the data gathered by different sensors.
The correlation step is completely general. In particular we have solved in an elegant way the problem occurring when several objects are viewed by different sensors. Reliability of sources as well as expert confidence values is introduced as discounting factors.
Even when the correlation coefficient does perform acceptable, there are usually better algorithms for image comparison. Typically the optimum choice of algorithms depends critically on general characteristics if the relevant images, and details of application.
The correlation coefficient is used for security applications such as surveillance, treaty verification, tamper detection using security seals, and tagging. Typically, the correlation coefficient is used to compare two images of the same object (or scene), taken at different times.
As for the conclusion step, due to the fact that the errors do not have the same impact depending on the decided object we designed a new approach that favours the decision for correlation in the case of ambiguity.

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