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A New Robust Estimator with Application to Image Analysis

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Abstract:- The field of computer vision is undergoing tremendous development in recent years. Computer vision concerns with developing systems that can interpret the content of natural scenes. Robust statistical methods were first adopted in computer vision to improve the performance of feature extraction algorithms at the bottom level of the vision hierarchy. These methods tolerate the presence of data points that do not obey the assumed model such points are typically called "outlier". Recently, various robust statistical methods have been developed and applied to computer vision tasks. Random Sample Consensus (RANSAC) estimators are one of the widely applied to tackle such problems due to its simple implementation and robustness. In this paper we propose a novel and highly robust estimator, called INAPSAC (Improved N Adjacent Points Sample Consensus). The performance of the proposed algorithm has been studied through the experimental study along with the existing algorithms in the context of RANSAC techniques under the characteristics such as number of corners detected in an image with various types and the processing time is also considered.

Keywords:- Robust Statistics-RANSAC-INAPSAC-Image-Feature Detection

I. INTRODUCTION

Computer vision systems begin with the process of detecting and locating some features in the input image. The degree to which a computer can extract meaningful information from the image is the most powerful key to the advance of intelligent image understanding systems. Our own visual system is superb in the qualitative extraction of information, but it is bad at accurate quantitative measurement, as opposite to the capability of a computer. Feature extraction plays a very important role to fill the gap between what we can get and what we want to have. In computer vision society, a feature is defined as a function of one or more measurements, the values of some quantifiable property of an object, computed so that it quantifies some significant characteristics of the object. One of the biggest advantages of feature extraction lies that it significantly reduces the information to represent an image for understanding the content of the image. Many computer vision algorithms use feature detection as the initial step, so as a result, a very large number of feature detectors have been developed. These vary widely in the kinds of feature detected, the computational complexity and the repeatability. In general these feature detectors may be classified into four types such as edges, corners, blobs and ridges. Image corner detection is an important task in various computer vision and image understanding systems, because corners are proven to be stable across sequences of images. A corner is a relatively important kind of localized two-dimensional image structure with a mathematical description.

In this paper we apply our newly proposed method INAPSAC in feature detection especially corner detection and also compared with several other existing methods. The brief discussion about the family of RANSAC techniques are given in section 2. The algorithm of newly proposed robust RANSAC method called Improved NAPSAC (INAPSAC) along with mathematical calculation is presented in section 3. In section 4 the performance of the INAPSAC algorithm is studied through an experiment with the existing RANSAC and NAPSAC methods. Section 5 contains a quick discussion about the work as well as the conclusion.

II. RANDOM SAMPLE CONSENSUS TECHNIQUES

Anton and et al (2005) uses the following strategy for the measured data has total of N samples with unknown fraction of inliers γ. To estimate true model parameters we would like to label data as outliers and inliers and estimate the model parameters from inliers only. As this labeling is initially unknown, RANSAC tries to find outlier-free data subset randomly, in several attempts. To maximize the probability of selecting sample without outliers RANSAC tests only samples of minimal size.

The RANSAC algorithm consists of *M* iteration of the following three steps:

- Random sampling m elements of the input data $S_k \subset x$
- Estimating hypothesis θ_k from S_k
- Measuring the hypothesis score, $R_k=R(\theta_k)$

After generation and evaluation of M hypothesizes, the one with highest score, $\max_{k=1,N}(R_k)$, is selected as the result of robust estimation. Given the expected fraction of inliers γ in the input data and the total number of samples *N*, the number of algorithm iterations *M* necessary to find the true model parameters with desired probability *P* can be calculated.

Myatt and et al. (2002) introduced the NAPSAC estimator. The algorithm of NAPSAC focused on the efficiency of the sampling strategy. The idea is that inliers tend to be closer to one another than outliers, and the sampling strategy can be modified to exploit the proximity of inliers. This might bring efficient robust recovery of high dimensional models, where the probability of drawing an uncontaminated sample becomes very low even for data sets with relatively low contamination of outliers. Non-uniform sampling has been shown to provide a theoretical advantage over uniform sampling, but will now be shown experimentally to be just as effective in high noise and higher dimensions. To demonstrate this, a simple enhanced sampling algorithm was created. The following algorithm can be used in place of the uniform point sampling process in any of the robust estimation algorithms.

- Select an initial point X_0 randomly from all points.
- Find the set of points, S_{x0}, lying within a hypersphere of radius r centered on X_0.
- If the number of points in S_{x0} is less than the minimal set size then fail..
- Select points from S_{x0} uniformly until the minimal set has been selected, inclusive of X_0.

The enhanced sampling algorithm was integrated with the RANSAC consensus set cost function to facilitate experimentation. This combination was named N Adjacent Points SAmple Consensus (NAPSAC).

III. IMPROVED N ADJACENT POINTS SAMPLE CONSENSUS (INAPSAC)

Myatt and et.al (2002) proved that the uniform point sampling may be failed in higher dimensions. So, it may be related to its neglect of the spatial relationship between the inlying data points. Using the distribution of the inlying data within the multi-dimensional space to modify the point sampling may improve hypothesis selection. Such models are already used to determine the quality of estimation. The method proposed here is to use a similar technique to select hypotheses through improved point selection. The proposed a new inlier identification scheme based on proximity in three dimensions spheres is as following. Let $\{X_1,X_2,\ldots,X_N\}$be the set of all data points (inliers and outliers). First assume that the initial data point x_0 has already been selected and that point lies on the manifold. So, therefore marginal density of inliers and outliers at a distance r from X_0 can be calculated. Then, by comparing these marginal densities, it can be determined whether selecting by proximity increases the probability of sampling inliers over uniform random sampling. To examine the worst case scenario, where the points are uniformly distributed on the manifold between limits $-t<x<t$ and $-t<y<t$, such that the probability density function of x and y are $p_i(x) = 1/2t$ and $p_i(y) = 1/2t$. Assume that inlier point coordinates are measured with error that satisfies Gaussian distribution with zero mean and standard deviation σ. This distribution is truncated $-t< z< t$, since $t>\sigma$, the truncation will have negligible effect on subsequent calculations. Thus, the joint probability density of the inliers is

$$p_i(x,y,z) = \begin{cases} \dfrac{1}{4t^2\sigma\sqrt{2\pi}}\exp\left(-\dfrac{z^2}{2\sigma^2}\right) & if\ -t<x<t, -t<y<t, -t<z<t \\ 0 & otherwise \end{cases}$$

The outliers are uniformly distributed in a 2-sphere centered on the origin radius t then the Probability density function of outliers is

$$p_o(x,y,z) = \begin{cases} \dfrac{1}{4\pi t^3} & if \quad \sqrt{x^2+y^2+z^2} < t \\ 0 & otherwise \end{cases}$$

Then the joint pdf of inliers and outliers is, $P(x,y,y)=\mu p_i(x,y,z)+(1-\mu)p_o(x,y,z)$.

In order to find the conditional probability density of selecting an inlying point from a given point on the manifold as a function of their mutual distance, a coordinate transform from Cartesian to Polar is required

$$P_i(r,\varphi) = Kr\exp\left(-\frac{r^2\sin^2\varphi}{2\sigma^2}\right)$$

where $K = \dfrac{1}{4t^2\sqrt{2\pi}}$

Then the marginal density of inliers is

$$m_i(r) = \int_o^{\pi} Kr\exp\left(-\frac{r^2\sin^2\varphi}{2\sigma^2}\right)\delta\varphi \quad .$$

However, using the trigonometric identities $\sin^2\varphi = \sin 2(\varphi + \pi)$ and $\sin^2\varphi = 1/2\,(1 - \cos 2\varphi)$ this can be rearranged to

$$m_i(r) = Kr\int_o^{2\pi}\exp\left(-\frac{r^2(\frac{1}{2}(1-\cos 2\varphi)}{2\sigma^2}\right)\delta\varphi$$

$$m_i(r) = Kr\int_o^{\pi}\exp\left(-\frac{r^2(1-\cos 2\varphi)}{4\sigma^2}\right)\delta\varphi$$

Integrating the above equation with respect to φ, we get

$$m_i(r) = 2Kr\exp\left(-\frac{r^2}{4\sigma^2}\right)\left[\pi I_0\left(\frac{r^2}{4\sigma^2}\right)\right]$$

where I_0 is the modified Bessel function of first kind. After simplifying, one the marginal density as

$$m_i(r) = \mu\frac{1}{t^2}\sqrt{\frac{\pi}{2}}\left[\frac{r}{\sigma}\exp\left(-\frac{r^2}{4\sigma^2}\right)I_0\left(\frac{r^2}{4\sigma^2}\right)\right]$$

The polar to Cartesian transformation of outliers is

$$P_0(r,\varphi)=\frac{3}{4\pi t^3}r$$

The marginal density of outliers is

$$m_o(r) = \int_0^{2\pi}\frac{3}{4\pi t^3}r\delta\varphi$$

Integrating the above equation w.r.t φ

$$m_o(r) = (\frac{3}{2t^3}r)(1-\mu)$$

As per Myatt et at (2002) as r increase, $m_i(r) \to \frac{1}{t^2}$. Consequently, if r_c denotes a distance at which both marginal densities are equal, then

$$r_c \approx \frac{2t}{3}\left(\frac{\mu}{(1-\mu)}\right).$$

The following INAPSAC algorithm is used in the place of sample selection.

- Select initial data point X_0 from U at random.
- Find the set of sample points R_{X_0} lying in a 3 dimensional hyper-sphere (2-sphere) of radius r centered on X_0.
- If the size of R_{X_0} is less than the minimal set size m-1 then fail
- Repeat the above steps until the minimal set has been selected including the point X_0.

This results in a cluster of points being selected from a ball. If the initial point, X_0, lies on the manifold, then the rest of the points sampled adjacently will theoretically have a significantly higher probability of being inliers. If there are not enough points within the hypersphere to estimate the manifold, then that sample is considered a failure.

IV. EXPERIMENTAL RESULT

This section presents the relative performance of INAPSAC with RANSAC and NAPSAC. The experiments were carried out using MATLAB, and tested with an image. The objective is to produce clean corner detection by extracting the principal features of the image. The original image with various types and the image with corners detected under different RANSAC techniques are given in figure and the processing time requirement for different RANSAC methods are listed in table.

Table I: Processing Time and Corners Detected with Various Type of Images

Type	**Size**	**Processing Time**			**No. of Corners Detected**		
		RANSAC	**NAPSAC**	**INAPSAC**	**RANSAC**	**NAPSAC**	**INAPSAC**
JPG	10 KB	0.0994	0.0460	0.0401	68	72	90
TIF	55 KB	0.0835	0.0322	0.0232	43	43	50
BMP	200 KB	0.1024	0.0420	0.0302	54	59	80

Table II: Type of Images Along with Corners Detected Under Various Methods

Type	JPG	TIF	BMP
Original Image			
RANSAC			
NAPSAC			
INAPSAC			

From the table it is observed that the processing time of INAPSAC consumes much less time than the other methods and the percentage of corners detected is more than the existing methods. While considering the type of images, one can detect more (actual) number of corners from JPG type image with the processing time is little bit high. From the experimental results, it is concluded that the INAPSAC method shows the better performance than RANSAC and NAPSAC.

V. CONCLUSION

Robust techniques are used by the computer vision communities for the past three decades. In fact, those most popular methods today are related to old methods proposed to solve specific image understanding or pattern recognition problems. Some of them were rediscovered only in the last few years. The best known example is the family of RANSAC to perform computer vision tasks. In this paper we have proposed an algorithm which is novel and highly robust estimators. Analyzed its properties through an experiment and applied it to detect the corners from the various types of images and is compared to several other methods. The experimental result shows that the proposed robust estimator is more accurate to detect the corners from an image with/without noise and less time consuming.

REFERENCES

[1]. Computer Vision System Toolbox, User Guide, MATLAB, R2012a.
[2]. Denis G. Pelli and et.,al, 2006, "Feature Detection and Letter Identification", Vision Research, 46, pp.4646–4674.
[3]. Fischler, M.A. and Bolles, R.C., 1981, "Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography", Commun. ACM, 24(6), pp.381-395.
[4]. Huber, P.J., 1972, "Robust Statistics", Wiley New York.
[5]. Mark.S.Nixon and Alberto.S.Aguado, 2002, "Feature Extraction and Image Processing", Newnes, A division of Reed Educational and Professional Publishing Ltd, Oxford.
[6]. Mohanna, F and F. Mokhtarian, 2001, Performance Evaluation of Corner Detection Algorithms under Similarity and Affine Transforms. British Machine Vision Conference (BMVC).
[7]. Myatt D.R, P.H.S Torr, S.J. Nasuto, J.M. Bishop, and R. Craddock, 2002, "NAPSAC: High noise, high dimensional robust estimation - it's in the bag". Proceedings of the 13th BMVC.
[8]. Oge Marques, 2001, "Practical Image and Video Processing Using MATLAB", John Wiley & Sons, Inc., Hoboken, New Jersey.
[9]. Rafael C.Gonzalez, Richard E.Woods and Steven L.Eddins, 2004, "Digital Image Processing Using MATLAB", Pearson Education Pte. Ltd, Singapore.
[10]. Tinne Tuytelaars and Krystian Mikolajczyk, 2008, "Local Invariant Feature detection", Computer Graphics and Vision, 3(3), pp.177-280.