Pattern Recognition 60 (2016) 849–862

Contents lists available at ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/pr

Accurately estimating rigid transformations in registration using a boosting-inspired mechanism

Yonghuai Liu [a], Honghai Liu [b], Ralph R. Martin [c], Luigi De Dominicis [d], Ran Song [e], Yitian Zhao [f,*]

[a] Department of Computer Science, Aberystwyth University, Ceredigion SY23 3DB, UK
[b] School of Computing, University of Portsmouth, Portsmouth PO1 3HE, UK
[c] School of Computer Science and Informatics, Cardiff University, Cardiff CF24 3AA, UK
[d] Diagnostics and Metrology Laboratory, UTAPRAD-DIM, ENEA Frascati 00044, Italy
[e] School of Computing, Engineering and Mathematics, University of Brighton, Brighton BN2 4GJ, UK
[f] Beijing Engineering Research Center of Mixed Reality and Advanced Display, School of Optics and Electronics, Beijing Institute of Technology, Beijing 100081, China

ARTICLE INFO

Article history:
Received 7 December 2015
Received in revised form
4 May 2016
Accepted 6 July 2016
Available online 8 July 2016

Keywords:
Feature extraction
Feature matching
Point match evaluation
Boosting-inspired
Rigid underlying transformation

ABSTRACT

Feature extraction and matching provide the basis of many methods for object registration, modeling, retrieval, and recognition. However, this approach typically introduces false matches, due to lack of features, noise, occlusion, and cluttered backgrounds. In registration, these false matches lead to inaccurate estimation of the underlying transformation that brings the overlapping shapes into best possible alignment. In this paper, we propose a novel boosting-inspired method to tackle this challenging task. It includes three key steps: (i) underlying transformation estimation in the weighted least squares sense, (ii) boosting parameter estimation and regularization via Tsallis entropy, and (iii) weight re-estimation and regularization via Shannon entropy and update with a maximum fusion rule. The process is iterated. The final optimal underlying transformation is estimated as a weighted average of the transformations estimated from the latest iterations, with weights given by the boosting parameters. A comparative study based on real shape data shows that the proposed method outperforms four other state-of-the-art methods for evaluating the established point matches, enabling more accurate and stable estimation of the underlying transformation.

1. Introduction

Nowadays, 3D shapes can be easily captured using laser scanners; their output is represented as sets of discrete points (see Fig. 1). However, such devices have a limited field of view, and parts of the object may occlude others, so a number of scans have to be captured from different viewpoints. Where two scans cover common parts of the object, we say that these two scans are *overlapping*, and the shapes in these two scans are called overlapping partial shapes. Once all scans have been captured, an important task is to analyze and fuse geometric (and possibly color) information in these scans. Matching common points in the scans allows them to be used to register the scans. This is done by estimating the underlying transformation that best aligns the two scans. Here, we consider the underlying transformation to be rigid, involving a rotation and translation, but our method is also applicable to non-rigid registration involving more general classes of transformations, such as thin plate spline deformations [8].

Feature extraction and matching (FEM) are widely used for various tasks: object registration [41], modeling [2], retrieval, and recognition [18], as they are applicable to shapes with varying complexities of geometry, varying degrees of overlap, and varying magnitudes of transformation. The SHOT method, based on a signature of histograms of orientations [41], is one of the best methods for the extraction and matching of features from overlapping partial shapes [4,17]. Even so, it usually unavoidably introduces mismatches amongst the established putative point matches (PPMs). In this approach, the random sample consensus (RANSAC) scheme [11] is used to reject mismatches and the unit quaternion method [7] is used to estimate the underlying transformation. However, the RANSAC scheme has a number of shortcomings, including a need to choose thresholds determining: whether a match is correct or a mismatch, when a good model has been found, and when to terminate the iterative process.

* Corresponding author.
E-mail addresses: yyl@aber.ac.uk (Y. Liu), honghai.liu@port.ac.uk (H. Liu), ralph@cs.cf.ac.uk (R.R. Martin), luigi.dedominicis@enea.it (L. De Dominicis), R.Song@brighton.ac.uk (R. Song), Yitian.Zhao@bit.edu.cn (Y. Zhao).

http://dx.doi.org/10.1016/j.patcog.2016.07.011
0031-3203/

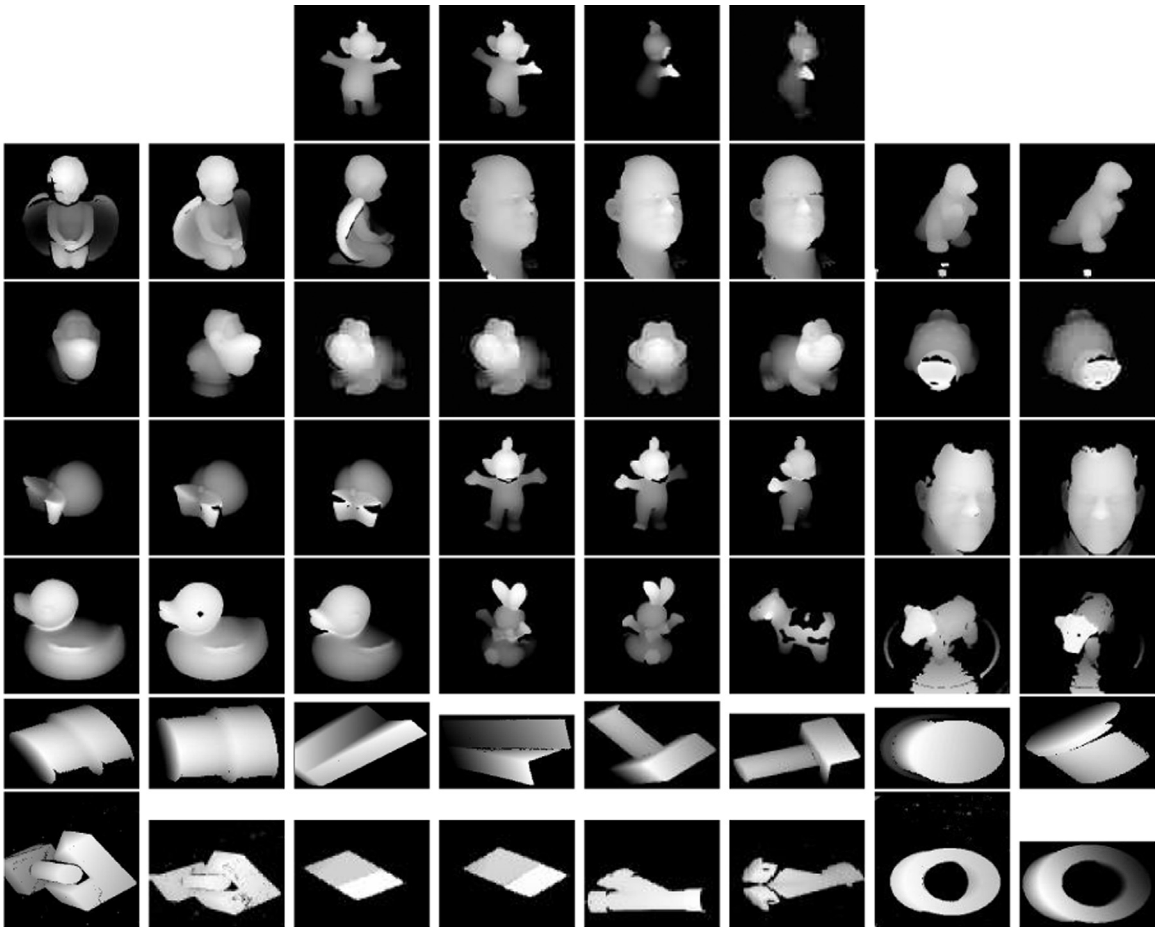

Fig. 1. Real freeform shapes used in testing [32]. From left to right: Row 1: tubby160, tubby140, tubby120, and tubby100. Row 2: angel0, angel40, angel80, rick0, rick36, rick72, dinosaur144, and dinosaur180. Row 3: bird60, bird100, frog0, frog20, frog40, frog80, lobster60, and lobster80. Row 4: peach240, peach260, peach280, tubby0, tubby20, tubby40, pat108, and pat144. Row 5: duck0, duck20, duck40, bunny0, bunny40, cow37, cow42, and cow45. Row 6: adapter2, adapter3, block3, block5, column2, column5, cap1, and cap5. Row 7: occl5, occl6, grnblk1, grnblk2, wye2, wye3, taperoll1, and taperoll2.

In this paper, we propose an alternative, novel, boosting-inspired method for evaluating the correctness of the established PPMs, with the aim of estimating as accurately as possible the underlying transformation. This estimate may then be used to initialize, for example, the SoftICP [23] variant of the iterative closest point (ICP) algorithm [7] for final refinement of the transformation. In particular, we want to investigate two problems: (i) to what extent the FEM can be used to register overlapping 3D partial shapes and how accurate the estimated underlying transformations from the matched point pairs can be, and (ii) whether our approach provides an initial estimate which is closer to the globally optimal solution than the one provided by the original method—if it does, it is more likely that the SoftICP algorithm will converge correctly to the global optimum, rather than a local optimum.

Our novel method is inspired by the widely used *adaptive boosting* learning and classification method (AdaBoost) [15] from machine learning which combines several weak learners. The AdaBoost method has various advantages over other learning methods such as decision trees. Firstly, as long as each weak learner is better than random guessing, the boosted learner will be a stronger learner with improved performance. It is easy to find such weak learners. Secondly, the learning process concentrates on the incorrectly classified instances and increases their weights. This avoids overfitting, while ensuring that the decision when to terminate the learning process is not critical. The boosting parameter plays a crucial role in determining the extent to which the weights of the incorrectly classified instances will be increased.

Clearly, data classification as performed by Adaboost, and point match evaluation, are two different problems: the former requires training data, but such training data is not available to the latter. The main idea of our boosting-inspired method is as follows. Evaluation of the established point matches is a data fitting problem. In this case, all the established PPMs belong to the same class but are treated as having different reliabilities, represented as a real number in the unit interval $[0, 1]$; the larger the number, the more likely we believe it to be correct. The proposed method focuses on estimating and updating these reliability values iteratively. After such reliabilities or weights have been initialized or estimated, the underlying transformation is determined in a weighted least-squares sense and the weighted average e_μ and standard deviation e_σ of the errors of all the PPMs can be calculated accordingly in each iteration. Then we construct an objective function for the estimation of the boosting parameters. This objective function minimizes the weighted average of e_μ over different iterations, with the weights set to the boosting parameters. To avoid the degenerate case where all the boosting parameters are zero, they are regularized by the Tsallis entropy in the framework of entropy maximization [16]. The boosting parameters have a closed form solution. To update the weights of the PPMs, we minimize the weighted average e_c of the modified squared registration errors of all the PPMs with the weights regularized by the Shannon entropy H_s in the framework of entropy maximization again and the two terms of e_c and H_s are balanced by the