Load identification using computer vision and FEM based particle filtering

Marcin Tekieli and Marek Słoński
Institute for Computational Civil Engineering, Cracow University of Technology
Warszawska 24 street, 31-155 Cracow, Poland
e-mail: mtekieli@l5.pk.edu.pl, mslonski@l5.pk.edu.pl

Abstract

This paper presents the design and implementation of a computer vision based application of particle filtering (PF), finite element method (FEM) and digital image correlation (DIC) to identify the magnitude and the position of a quasi-static concentrated load for a laboratory aluminum frame [1]. This is done by solving the inverse problem. The essence of the research is to combine three powerful computational methods - DIC for full-field displacement measurements with high accuracy, FEM for structural analysis and PF for sequential parametric estimation. The effectiveness of the proposed method was tested on the task of estimating load magnitude and position applied to the aluminum frame model. The results of an exemplary analysis are presented.

Keywords: particle filtering, finite element method, digital image correlation, computer vision, inverse problem

1. Introduction

The problem of load identification is a very important and difficult class of inverse problem in structural mechanics because direct measurements of the forces are not always feasible, e.g., excitations of wind and seismic. As a result, an indirect estimation for the excitation forces is frequently employed based on a set of measurements of static and/or dynamic responses [3].

In the proposed approach, data are collected using computer vision system with high resolution industrial camera. This offers the potential to acquire structure performance data with no need of installation of conventional sensors, lasers or other devices. For the full-field displacement measurements digital image correlation (DIC) is used. It is an optical method that is widely used in many areas of science and engineering to measure deformation of an object surface [2]. A particle filter, also known as sequential Monte Carlo (SMC), is a sequential estimation technique for nonlinear models and non-Gaussian observations and it overcomes some limitations of nonlinear Kalman filters [1].

2. Full-field displacement measurements

The application of digital image correlation for displacement measurements in a whole structure or a complex model is rather rare. This is due to difficulties in specifying areas of the specimens, because each video frame contains mostly background instead of construction elements.

The proposed method solves this problem by using special markers, very easy to prepare and cheap to manufacture. Interior of the marker is composed of two kinds of pixels - whites and in the color of markers border. They are set randomly and allow subsequent use of DIC to track the location of the marker and to determine its movements. Markers localization is obtained by pointing the mouse cursor. It is also possible to automatically detect markers using particle filtering which is widely presented in [4]. Markers are placed in the characteristic points of the structure - at nodes or inside elements, see Fig. 1 and the resolution of the vision measurements was set to $0.15mm$.

3. Load identification

The main part of the system is the algorithm responsible for load parameters estimation. The aluminum frame was loaded by application of a quasi-static vertical or horizontal force applied to the upper bolt. The first set of tests was carried out to estimate the load magnitude with known load position. In this case, each particle represents the load magnitude initially drawn from $[-200N; 200N]$ interval using uniform distribution. Weight assigned to each particle is higher, if the displacements obtained from FE model are more similar to the displacements in each of marked points obtained using vision system. At this stage, the density function for a Gaussian distribution is used, given by following formula:

$$\phi(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{(-\frac{(u'-u)^2}{2\sigma^2})} \quad (1)$$

where the parameters u', u are displacements obtained from FE model and from vision system, respectively. The parameter σ is the standard deviation of the normal distribution.

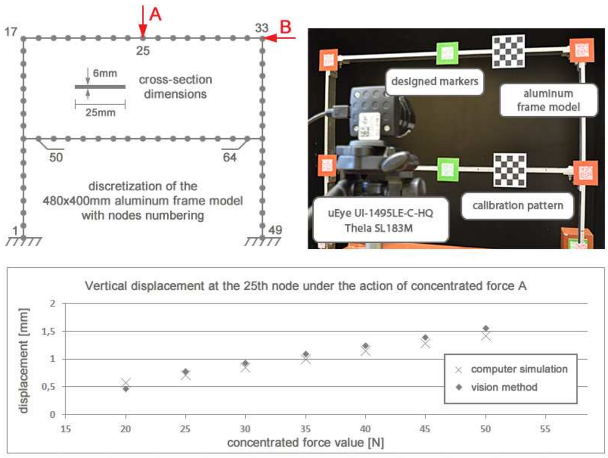

Figure 1: Frame FE model, test stand and plot of measured and computed displacements under the action of the vertical force.

[1]The authors would like to thank The Faculty of Civil and Environmental Engineering of the Rzeszow University of Technology for sharing the aluminum frame model.

After the weights normalization, a new population of the particles is created using a modified roulette wheel method. In addition, to increase the efficiency of the algorithm, the values of the particles are slightly modified with the noise value from $[-f_r; f_r]$ interval, where f_r is the parameter called *resampling factor*. At every iteration, a new set of particles is created which contains mostly particles with higher weights. Iterations are performed until the values assigned to some of the particles are out of the interval called *population size*.

The second set of tests was carried out to estimate the position of the load with known magnitude. This process is similar to the estimation of the load magnitude. However in this case, each particle is assigned to a particular degree of freedom (DOF) initially drawn from $[1; 3n]$ interval containing integer values, where n is the number of FE used in the FE model.

The most complex set of tests consisted of estimating the load magnitude and its position simultaneously. At this stage each particle contains two parameters – the magnitude and the position of the load. Initially, values of these parameters are drawn as before without any prior knowledge for each particle. Unfortunately, this type of problem cannot be solved without some modifications and improvements of the main algorithm described before.

One of the improvements applied at the load position estimation process is to change the way of resampling particles. Particle parameter associated with load position cannot be modified arbitrarily at each iteration. It is very important to change this parameter only with multiples of 3 when we use frame elements in the FEM model. It is related to the number of DOFs assigned to every node. Modifying this parameter by other values causes loss of convergence and increase of incorrect results.

Another significant modification of the algorithm is multi-stage estimation of the load parameters. Due to complexity of the problem it is hard to obtain a good convergence of the solution using a large number of particles. Reducing the number of the particles, in turn, may lead to a significant increase of iterations number due to insufficient covering of the solution space by particles. Multi-stage estimation consists of gradual narrowing of the solution space. At each stage, the number of particles is reduced and the particles parameters are drawn from a narrowed interval. This leads to decreasing of the relative mean error for load magnitude estimation from about 20% to 10%. The load position is determined with accuracy of twice size of the finite element used in the model. This means that in the last iteration when the stop condition of the algorithm is satisfied, all of the particles are assigned to the corresponding degrees of freedom of three adjacent nodes.

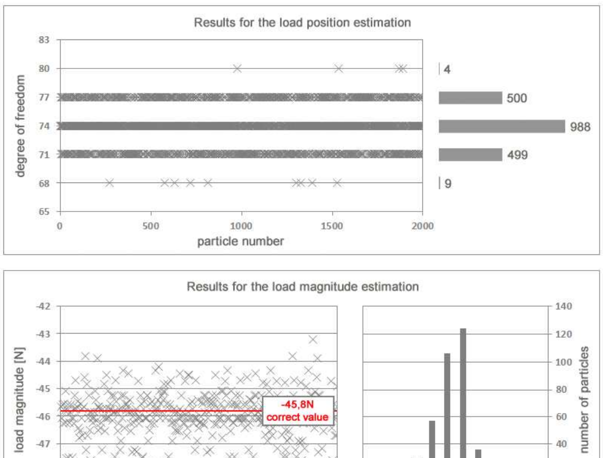

Figure 2: Results for simultaneous estimation of the load position and magnitude using particle filter.

Next important extension of the algorithm is the application of least squares method to select only one DOF from the range estimated earlier. The load with the magnitude equal to the half of the estimated value is applied at every DOF from the estimated range. DOF at which the applied load generates the displacement most similar to the displacement obtained from the vision system is chosen. This results in further decrease of the relative mean error for the load magnitude estimation to about 5%. Selection of the best fitted DOF allows to solve ambiguous problems when the horizontal load is applied to the frame model.

It is also possible to further reduce the error value by solving the problem of the estimation of the load magnitude with known load position which is determined at previous steps. The value of the relative mean error in this case is between 2% and 3%. The results for the model with 64 FEs can be seen in Fig. 2. The force was applied in the middle of the upper bolt and the 74th DOF corresponds to the element of the nodal forces vector in the vertical direction. The set of 2000 particles was used in the first stage of the algorithm and finally, the number of particles was reduced to 400 for the last step to correct the load magnitude.

4. Final remarks

The discussed identification problem was also solved with two other methods. The Kalman filter (KF) was used to estimate the load magnitude in the continuous solution space and the simple genetic algorithm (SGA) was applied to solve the localization problem in the discrete solution space. The obtained results are shown in Fig. 3. However, it is important to note that this combined approach cannot be used to estimate efficiently these two parameters simultaneously. Moreover, it is also much more difficult to implement SGA based solution of the discussed identification problem in comparison with particle filters.

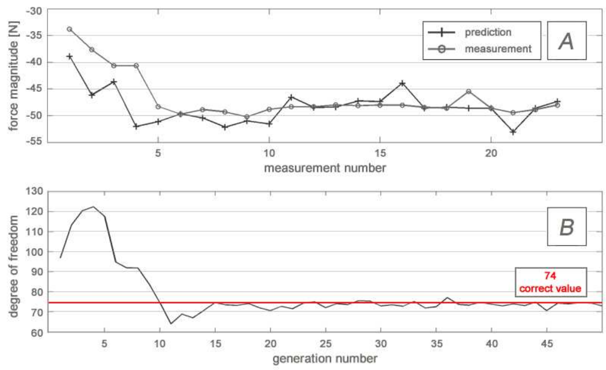

Figure 3: Results of estimation of load magnitude using KF (top) and estimation of load position using SGA (bottom).

References

[1] Bishop, C.M., *Pattern Recognition and Machine Learning*, Springer-Verlag, 2006.

[2] Malesa, M. et al., Monitoring of civil engineering structures using digital image correlation technique, *In: EPJ Web of Conferences*, Volume 6, EDP Sciences, 2010.

[3] Uhl, T., The inverse identification problem and its technical application, *Arch. of App. Mech.*, 77(5), pp. 325–337, 2007.

[4] Tekieli, M., Słoński, M., Computer Vision Based Method for Real Time Material and Structure Parameters Estimation Using Digital Image Correlation, Particle Filtering and Finite Element Method, *Artificial Intelligence and Soft Computing*, LNCS, vol.7894, pp.624–633, Springer, 2013.