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Raziskave možnosti uporabe neparametrične regresije v lokatorjih izvorov akustične emisije

Application of Non-parametric Regresion in Locators of Acoustic Emission Sources

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Članek opisuje lokator izvorov akustične emisije (AE), ki je zasnovan na uporabi neparametrične regresije. Lokator je sestavljen iz mreže zaznaval, ure, ki določa čase zaznave akustične emisije na posameznih zaznavalih, in računalnika. Za delovanje lokatorja sta značilni faza učenja in faza analize. Med učenjem zaznavala ob določenem času zaznajo AE, z uporabo ure pa dobimo časovne zakasnitve med njimi. V računalniku predstavimo izbruh AE z vektorjem, ki ga sestavljajo časovne zakasnitve med zaznavali in ustrezne koordinate izvora. V tej fazi s preizkusi pridobimo množico umeritvenih podatkov in jih shranimo v podatkovno bazo v pomnilnik računalnika, ki pomeni izkustveni model pojava AE. Po učenju lahko lokator določa lego izvora iz izmerjenih časovnih zakasnitev z neparametrično regresijo zasnovano na tej podlagi. V članku je prikazano, da lahko isti lokator uporabimo na vzorcih različne oblike in za različne razporeditve zaznaval brez spremembe programa delovanja.

This paper describes a locator of acoustic emission sources based on a non-parametric regression procedure. It includes a network of AE sensors, a triggered clock and PC. A learning and an analysis phases are characteristic of the operation of a locator. During learning, AE bursts in the specimen are detected by sensors, while the clock measures the time delays between them. In the computer, a particular AE burst is represented by a vector comprised of time delays and corresponding source coordinates. In this phase, a set of experiments provides prototype data which are stored in the computer and represent an empirical model of the AE phenomenon. After learning, the locator is capable of determining the source position from measured time delays throughout the procedure of non-parametric regression. It is shown in the paper that the same locator is applicable on samples of various geometrical properties and with various sensor network configurations.

0 UVOD

Zahteve po vrhunski kakovosti tehničnih konstrukcij narekujejo uporabo neporušnega testiranja za pregled materiala [2], [6]. Med različnimi postopki neporušnega preizkušanja je metoda zaznavanja poškodb z ultrazvokom zelo razširjena. Trenutno se v ta namen uporabljata dva različna postopka zasnovana na zaznavanju odbitega ultrazvoka in akustične emisije. Prvi postopek je primeren za lociranje in proučevanje obstoječih poškodb v materialu. Drugi postopek temelji na analizi akustične emisije, ki se pojavi zaradi spreminjanja lastnosti snovi [3], [5], [6]. V obremenjeni snovi pride do porajanja lokalnih nestabilnosti, pri katerih se del nakopičene elastične energije pretvori v zvočno. Z zaznavanjem in analizo emitiranega zvoka lahko dobimo podatke o spremembi lastnosti snovi. Poleg tega lahko s triangulacijskim postopkom določimo lego nastale spremembe, ki v trdni snovi pogosto pomeni razvoj mikroskopske poškodbe.

0 INTRODUCTION

The high quality of technical constructions demands non-destructive testing of materials [2], [6]. Among various non-destructive methods, the characterization of defects by ultrasound is widely applied. Two different methods are applied for this purpose: ultrasonic defectoscopy and analysis of acoustic emmision (AE). The first method is based on the scattering of ultrasound and is suitable for the location and characterization of flaws in materials, while the second method is applicable when the properties of the materials are changing [3], [5], [6]. The development of instabilities in the loaded materials is accompanied by a conversion of stored elastic energy into sonic energy that is emitted from the source in waves. Information about changes of material properties can therefore be obtained by detection and analysis of the emitted sound. In addition, it is possible to determine by triangulation method the location of the instability, which often represents a microscopic developing defect. The triangulation method is based on measurement of time delays between AE bursts detected by sensors at different positions on a test object.

Metoda temelji na merjenju razlik med časi, ko posamezna zaznavala zaznajo izbruhe akustične emisije. Iz izmerjenih časovnih razlik je mogoče pri paličnih in preprostih ravninskih preizkušancih analitično določiti lego nastale spremembe. Na palici z zaznavaloma na konceh določimo koordinato izvora zvoka z izrazom [3], [6]:

$$x = \frac{c\,\Delta t}{2} + \frac{L}{2} \qquad (1).$$

Pri tem so: x — razdalja poškodbe od roba elementa, c — hitrost širjenja zvoka v palici. Δt — čas preleta zvoka med zaznavaloma in L — razdalje med zaznavaloma. Iz izmerjene časovne razlike lahko določimo koordinato x, če poznamo hitrost širjenja zvoka c. V ta namen lahko vzbudimo izvor zvoka pri enem od zaznaval in določimo čas preleta t_L dolžine L. Potem je:

$$x = \frac{\Delta t}{t_L}\,\frac{L}{2} + \frac{L}{2} \qquad (2).$$

Pri ploskovnem določanju lege izvora zvoka se račun bistveno spremeni. Po predpostavki, da se od izvora širi krožni val, uporabimo kvadratne enačbe za opis odvisnosti med časom potovanja zvoka od izvora do i-tega zaznavala in razlikami koordinat izvora ter zaznavala:

$$(x_i - x)^2 + (y_i - y)^2 = c^2(t_i - t_0)^2 \qquad i = 1 \ldots S \qquad (3).$$

Pri tem sta (x_i, y_i) koordinati i-tega zaznavala in (x, y) koordinati izvora AE. t_i označuje čas vzbuditve i-tega zaznavala.

Čas nastanka vala t_0 ni znan, izmerimo pa lahko velikost časovnih zakasnitev $\Delta t_{ij} = t_i - t_j$. Velikost zvočne hitrosti c običajno tudi ni poznana, vendar jo lahko določimo z umeritvenim postopkom, podobno kakor na palici. Koordinati izvora (x_i, y_i) lahko v načelu določimo iz sistema nelinearnih enačb (3), pri čemer moramo najprej izločiti neznano vrednost t_0. Problem splošno ni rešljiv, lahko pa ga rešimo analitično za nekatere preproste postavitve zaznaval, kakor na primer za kvadratno anteno. Vendar pa pogosto tudi v takšnih preprostih primerih ne dobimo rešitve, ki bi veljala za celotno območje okoli zaznaval [1], [2].

Še dokaj bolj zapleteno in zato prav tako splošno nerešljivo pa je določevanje koordinat zaznaval v primeru prostorskega preizkušanca. Zaradi tega je predvsem pri določanju lege izvora zvoka na ploskovnih in prostorskih preizkušancih treba najti metodo, s katero bi se izognili analitičnemu določevanju koordinat izvora. Cilj tega prispevka je pokazati, da je v ta namen primeren izkustveni opis naravnih pojavov, ki temelji na neparametrični regresiji.

For linear and simple planar arrays of sensors (antenas) on continuous objects the location of the AE source can be determined analytically. For a stick-like object with a sensor placed at each end the following relation determines the source position [3], [6]:

$$x = \frac{c\,\Delta t}{2} + \frac{L}{2} \qquad (1).$$

Here x denotes the distance of the source from the edge of the object, c is the sound velocity, Δt is the time delay between signals detected by the two sensors spaced for L. From the measured time delay, the coordinate x can be determined if c is known. For this purpose we can simulate the AE source at one sensor and measure the time of flight t_L over the distance L. It follows that:

$$x = \frac{\Delta t}{t_L}\,\frac{L}{2} + \frac{L}{2} \qquad (2).$$

In a planar location case this expression is more complex. By taking into account that the emitted sound is propagated as a circular wave from the source we get a quadratic relation between the distance and time of flight from the source to the sensor:

$$(x_i - x)^2 + (y_i - y)^2 = c^2(t_i - t_0)^2 \qquad i = 1 \ldots S \qquad (3).$$

Here (x_i, y_i) and (x, y) denote the coordinates of the i-th sensor and the AE source respectively, and t_i denotes the arrival time of AE signal to the i-th sensor.

The time of emission t_0 is not known, only the diferences are measurable $t_i - t_j$. The sound velocity c is also not known, but it can be determined by a calibration procedure, as in the linear case. The source coordinates can be determined by solving the above system of equations. A general solution of this nonlinear system of equations is not known. However, for simple configurations of sensor arrays, such as is for example a square antenna, it can be expressed analytically. But even in then, the location algorithm may not always be applicable in the entire region around the sensors [1], [2].

A still more complicated, and also generally unsolved, location problem is met when determining the source coordinates on a spatial test object. We are thus looking for a new location method by which the analytical determination of the AE source coordinates could be avoided, especially in the case of planar and spatial objects. The aim of this paper is to show how the empirical description of natural phenomena based on non-parametric regression can be applied for this purpose.

1 POVEZAVA MED IZKUSTVENIM OPISOM NARAVNIH POJAVOV IN DOLOČANJEM LEGE IZVORA ZVOKA

Formule za računanje lege izvora zvoka na linijskem kakor tudi na ploskovnem preizkušancu pokažejo, da je zato potreben podatek t_L, ki opisuje hitrost zvoka v snovi. Določimo ga lahko na podlagi poznavanja lastnosti snovi, vendar pa v praksi večinoma uporabljamo neposredno umeritev. Lahko jo izvedemo z istim inštrumentom, kakršnega uporabljamo za določitev lege izvora zvoka. Podobno kakor določimo čas za prelet razdalje med obema zaznavaloma na palici, tudi meritve časovnih zakasnitev med zaznavali na ravninskem in prostorskem vzorcu podajo neznani parameter t_L. Enako lahko izmerimo časovne zakasnitve pri več postavitvah testnega vzorca in jih shranimo skupaj s koordinatami izvora v podatkovni bazi. S tako razširjenim umeritvenim postopkom lahko ocenimo lego izvora brez reševanja nelinearnih enačb, ki opisujejo širjenje valovanja. To dosežemo s primerjanjem časovnih zakasnitev, izmerjenih na neznanem izvoru zvoka, z zakasnitvami, ki smo jih dobili s simuliranjem izvora na različnih mestih. Sklepamo lahko, da ima neznani izvor približno enako lego kakor tisti simulirani izvor, pri katerem smo dobili najbolj podobne časovne zakasnitve. Tako lahko prevedemo triangulacijski postopek določanja koordinat v primerjanje podobnosti med podatki, ki jih izmerimo na neznanem izvoru, in tistimi, ki so shranjeni v bazi umeritvenih podatkov [4].

Opisana možnost je temelj metode, ki jo želimo prikazati v tem prispevku. Poglavitni namen je podatke, pridobljene z razširjenim umeritvenim postopkom, vključiti v splošni izkustveni model, s katerim so koordinate izvora *AE* in časovne zakasnitve medsebojno povezane s preslikavo:

$$f : \Delta t_l \rightarrow x, y \qquad (4).$$

Preslikava f dejansko opisuje izkustveni zakon povezave med časovnimi zakasnitvami Δt_l in koordinatami izvora (x, y). Ko preslikavo poznamo, lahko v nadaljnjih meritvah izmerimo le časovne zakasnitve, iz teh pa po primerjanju delnih rezultatov z zgrajenim modelom določimo koordinate. Zato je glavni problem poiskati metodo, s katero lahko splošno opišemo povezanost empiričnih podatkov.

V ta namen uporabimo postopek neparametrične regresije [4]. Predpostavimo, da lahko opazovani pojav opišemo s končnim številom eksperimentalnih podatkov, ki sestavljajo naključni vektor. V našem primeru je sestavljen iz dveh delnih vektorjev, od katerih eden vsebuje časovne zakasnitve, drugi pa ustrezne koordinate izvora *AE* [4].

1 RELATION BETWEEN THE EMPIRICAL DESCRIPTION OF NATURAL PHENOMENA AND SOURCE LOCATION

Location formulae include the time of flight t_L which describes the sound velocity c. It can be determined from the material parameters, but in practical testing, it is usually calibrated experimentally. The calibration procedure can be performed on the same instrument (locator) as it is applied for the *AE* source location. As in the measurement of the time of flight between two sensors placed on a stick, the measurement of time delays between sensors on planar or spatial arrays can provide the unknown parameter t_L. Furthermore, we can also measure time delays for *AE* sources simulated at other positions of the test sample with the system and store them together with source coordinates as components of vectors in some data base. By such an extended calibration procedure, we can provide empirical information for the solution of location problems without using analytical treatment of the nonlinear equation describing the wave propagation. We can avoid calculating the solution of this equation by comparing the delay times generated by an *AE* source at an unknown position with the delay times corresponding to various simulated *AE* sources. We can then infer that the unknown *AE* source coordinates approximately correspond to the stored coordinates of the simulated source which has the most similar time delay components. By such a treatment we can convert the analytical treatment of a triangulation problem into an associative estimation of source position based on comparison with empirical data obtained by the calibration procedure [4].

The method described above is the basis of the empirical solution of the location problem that is demonstrated in this paper. Our basic task is to decribe how the data obtained by extended calibration can be incorporated into a general empirical model that represents the mapping from time delays Δt_l to source coordinates:

The mapping f represents an empirical natural law. If this law is known, we can apply it to determine the source position from the measured time delays. The fundamental problem is, therefore, to formulate a method by which the transition from the data base to the mapping can be performed.

For this purpose, we apply non-parametric regression [4]. We assume that the phenomenon under consideration can be described by a finite number of experimental samples, each of which represents a sample of a random vector. This vector is comprised of two partial vectors, the first containing time delays and the other representing the source coordinates. In the case when time delays are measured, then non-parametric regression makes feasible estimation of the missing complementary components which are the source coordinates [4].

Postopek neparametrične regresije nato omogoči, da lahko pri poznanem delnem vektorju določimo manjkajoče podatke na podlagi primerjave delnega vektorja z ustreznimi komponentami vektorjev izkustvene baze, ki jo zgradimo v razširjenem umeritvenem postopku [4]. S tem nadomestimo analitični model, ki sloni na fizikalnem opisu širjenja zvoka z izkustvenim modelom oziroma neparametrično regresijo.

2 TEORETIČNE OSNOVE NEPARAMETRIČNE REGRESIJE

Glavni namen empiričnega modeliranja naravnih zakonov je prilagoditi danim podatkom sistem za obdelavo informacij, s katerim je mogoče na podlagi okrnjenih podatkov oceniti manjkajoče podatke o opazovanem pojavu [4]. V ta namen lahko uporabimo bodisi analitične metode ali pa analogne metode, s katerimi ustrezni naravni zakon prevedemo v lastnosti primerno izbranega sistema. Tipični primeri prve vrste so razne formulacije fizikalnih zakonov, npr. zakon, ki opisuje prosti pad. Primeri druge vrste pa so mehanski modeli, s katerimi eno spremenljivko prevedemo v drugo, kakršna je npr. menzura z označbami za maso snovi. Z razvojem elektronike se je odprla možnost avtomatičnega izvajanja meritev in modeliranja naravnih zakonov z uporabo elektronskih sistemov. Najbolj uporaben v ta namen je digitalni elektronski računalnik, ki pa mu moramo s primernim programom odpreti možnost modeliranja izbranega pojava na podlagi empiričnih podatkov. Cilj naše obravnave je pokazati, kako lahko dokaj splošno pridemo do napotkov za program, ki omogoča modeliranje naravnih pojavov. Metoda je bila širše opisana drugje [4], tu pa jo bomo le na kratko povzeli.

Predpostavimo, da lahko preizkus, izveden pri opisovanju fizikalnega pojava, izčrpno opišemo s končnim številom spremenljivk x_I, ki jih predstavimo kot vektor:

$$X = (x_1, x_2, \ldots, x_I) \tag{5}.$$

Spremenljivke x_I običajno izmerimo z naborom zaznaval in jih nato prevedemo v digitalizirane podatke, ki jih obdelamo z računalnikom. Celoten preizkus nato sestavimo iz dveh delnih preizkusov, pri katerih lahko nepopolne podatke predstavimo z delnima vektorjema: $G = (x_1, x_2, \ldots, x_M; \emptyset)$ in $H = (\emptyset; x_{M+1}, x_{M+2}, \ldots, x_I)$. Pri tem pomeni simbol $\emptyset$ podatke, ki v vektorju niso specificirani. Celoten podatkovni vektor lahko sestavimo iz delnih vektorjev:

For this purpose the distance between some given partial vector and the partial vectors of the database is determined and the complementary partial vector is associatively estimated based on some measure of similarity [4]. By this approach, we substitute an analytical model stemming from the physical description of sound propagation with an empirical model based on non-parametric regression.

2 THE THEORETICAL BASIS OF NON-PARAMETRIC REGRESSION

The basic task of empirical modeling of natural laws is to adapt an information processing system to given empirical data by which some missing data about the observed phenomenon can be estimated from the given partial data. For this purpose, we can apply either analytical or analog methods. Typical examples of the first kind are various formulations of physical laws, such as the law of free fall. In the the second method, the natural law is converted into properties of some real system. For this purpose, some kind of calibration is applied. Examples of this kind are various mechanical models capable of transforming one variable into another, such as a water container with marks for weight which represents the relation between the volume and the mass in the container. Development of electronics has offered systems capable of automatic measurements and modeling of natural laws. A computer appears to be most applicable for this purpose, although we have to provide a software capable of modeling the phenomenon on the basis of empirical data. In the following, show how one can proceed to the formulation of a program applicable for empirical modeling of natural phenomena. The principle has been thoroughly described elsewhere, [4] so only the most important steps are given here.

Let us assume that the outcome of the experiment applied for characterization of phenomenon can be completely described by a finite number of variables x_I represented by the vector:

The data x_I are usually detected in the experiment by a set of sensors and transferred in a digital form to a computer for. We consider the complete experiment comprised of two sub-experiments, the results of which are described by two truncated vectors: $G = (x_1, x_2, \ldots, x_M; \emptyset)$ and $H = (\emptyset; x_{M+1}, x_{M+2}, \ldots, x_I)$. Here the symbol $\emptyset$ denotes data that are not specified. The complete data vector is then comprised of partial ones:

$$X = G \oplus H = (x_1, x_2, \ldots, x_M, x_{M+1}, x_{M+2}, \ldots, x_I \tag{6}.$$

Pri analizi *AE* pomeni vektor G podatke, pridobljene iz signalov, ki jih dajejo zaznavala akustične emisije in ustrezna obdelava signalov. V našem primeru so to časovne zakasnitve Δt_I. Vektor H označuje podatke o izvoru, ki opisujejo lego ali vrsto poškodbe. Vektor X nadalje obravnavamo kot naključno spremenljivko. Njene lastnosti opišemo z gostoto porazdelitve verjetnosti:

In an *AE* experiment, vector G represent the data acquired by the detection of ultrasonic signals while vector H represents the position or the kind of the *AE* source. In our case, the components of vector G describe the time delays Δt_I and vector H represents the source coordinates. Vector X is further treated as a random variable described by the probability density function:

$$f(X) = \frac{d^I P}{dx_1 dx_2 \ldots dx_I} \tag{7},$$

To moramo oceniti na podlagi izkustvenih podatkov, začasno pa vzemimo, da je znana. Predpostavimo, da je delna informacija o pojavu podana z vektorjem G. Glavni problem je, kako priti do preostalih $(I-M)$ neznanih komponent, ki jih vsebuje komplementarni vektor:

Later, we describe how it can be estimated from the empirical data, but at present we consider it to be the known. Let us now assume that the partial information about the phenomenon is given by vector G. The main problem is to find the remaining $(I-M)$ unknown components.

$$H = (x_{M+1}, x_{M+2}, \ldots, x_I) \tag{8}.$$

Zaradi povezanosti komponent vektorja X so lastnosti vektorja H v splošnem odvisne od podanega vektorja G. Kot optimalno cenilko povezave izberemo funkcijo:

The components of vector X are generally correlated, so the properties of vector H are related to the properties of vector G. As the optimal estimator of the relation we utilize the function:

$$\hat{H} = \hat{H}(G) \tag{9},$$

ki minimizira naključni raztros oziroma napako ocene:

which minimizes the mean square error:

$$D = E\left[(H - \hat{H})^2\right] = \int \left[H - \hat{H}(G)\right]^2 dP(X) \tag{10}.$$

Tu je $dP(X)$ povezana verjetnost:

Here $dP(X)$ denotes the joint probability:

$$dP(X) = f(X) dx_1 dx_2 \ldots dx_I = f(G \oplus H)\, dG\, dH \tag{11}.$$

$\hat{H}(G)$ je neznana funkcija, ki jo lahko določimo z variacijskim postopkom. Predpostavimo, da je optimalna cenilka $\hat{H}_0$. Funkcijo $\hat{H}(G)$ lahko izrazimo kot:

The unknown function $\hat{H}(G)$ can be determined by the calculus of variation. Let us denote the optimal estimator as $\hat{H}_0$. The function $\hat{H}(G)$ can now be written as:

$$\hat{H}(G) = \hat{H}_0(G) + aV(G) \tag{12}.$$

Konstanta a pomeni amplitudo, $V(G)$ pa poljubno variacijo $\hat{H}(G)$. S tem postane napaka D funkcija amplitude a. Zahtevamo, da mora imeti minimum pri $a = 0$, kar da:

Where the constant a denotes the amplitude and $V(G)$ an arbitrary variation of $\hat{H}(G)$. The error D thus become a function of the amplitude a and we require that $\hat{H}$ has a minimum for $a = 0$, or:

$$\frac{dD}{da}\Big|_{a=0} = 0 = -2\int\int \left[H - \hat{H}(G)\right] V(G) f(X)\, dG\, dH \tag{13}.$$

Ker je variacija $V(G)$ odvisna le od M komponent, ki opisujejo delni vektor G, lahko zapišemo:

Since the variation $V(G)$ depends only on M components describing vector G, we write:

$$\int V(G)\, dG \int \left[H - \hat{H}_0(G)\right] f(G \oplus H)\, dH = 0 \tag{14}.$$

Zaradi poljubne oblike variacije $V(G)$ je enačba vedno izpolnjena le, če je drugi člen enak nič:

The variation $V(G)$ is assumed to be arbitrary, so the condition is satisfied if the second factor vanishes:

$$\int \left[H - \hat{H}_0\right] f(G \oplus H)\, dH = 0 \qquad (15).$$

Optimalna cenilka je tako podana s pogojnim povprečjem:

The optimal estimator is described by the conditional average:

$$\hat{H}(G) = \int H f(H|G)\, dH = E\left[H|G\right] \qquad (16).$$

Pri tem je gostota pogojne verjetnosti podana z enačbo:

Here, the conditional probability density is defined by the equation:

$$f(H|G) = \frac{f(G \oplus H)}{f(G)} = \frac{f(G \oplus H)}{\int f(G \oplus H) dH} \qquad (17).$$

Funkcija $f(H|G)$ je osnova Bayesovih klasifikatorjev, ki jih uporabljamo pri različnih metodah razpoznavanja vzorcev [7]. Naša metoda se od teh metod razlikuje v tem, da nas ne zanima klasifikacija posameznih vektorjev, temveč obravnavamo podani vektor G kot vhodno spremenljivko v splošno nelinearen sistem z izhodno spremenljivko $\hat{H} = \hat{H}_0(G)$. Odzivna funkcija sistema je tako opisana z optimalno cenilko $\hat{H}$. Takšna metoda spominja na analitično modeliranje pojavov z uporabo Greenove funkcije, le da je v našem primeru model zgrajen izkustveno z optimalno statistično cenilko, ki je lahko tudi nelinearna [4].

Pričakujemo lahko, da se bo z večanjem števila podanih komponent M in manjšanjem števila neznanih komponent $(I–M)$ uporabnost modela izboljševala.

V izkustvenem opisu opazovanega pojava funkcija porazdelitve verjetnosti ni znana analitično, temveč jo moramo oceniti izkustveno iz izmerjenih podatkov. Predpostavimo, da množica vzorčnih vektorjev X_1, X_2, ..., X_N opisuje rezultate N neodvisnih, vendar statistično enakovrednih preizkusov. Ti podatki sestavljajo izkustveno podatkovno bazo. Vsakemu preizkusu nato pripišemo statistično utež $1/N$, gostoto verjetnosti pa izrazimo z:

The function $f(H|G)$ is the basis of so called Bayesian classifiers, which are used in different methods of pattern recognition [7]. Our approach differs from these methods in the fact that we are not interested in the classification of vectors, but we treat the given vector G as an input to some information processing system with the output $\hat{H} = \hat{H}_0(G)$. The optimal estimator thus represents the response function, so the described approach is reminiscent of analytical modeling of mechanical systems by Green's function. The main difference is that in our case the model is built empirically by an optimal statistical estimator, which can be also non-linear [4].

We expect the applicability of the model generally to increase with an increasing number of given components M and a decreasing number of unknown components $(I–M)$.

In empirical description of natural phenomenona, the probability distribution function is not given analytically, but must be estimated from experimental data. We assume that a set of sample vectors X_1, X_2, ... X_N represents the results of N independent but statistically equivalent prototype experiments. A weight of $1/N$ is therefore assigned to each experiment, and the density function is then described as:

$$f(X) = \frac{1}{N} \sum_{n=1}^{n} \delta(X - X_n) \qquad (18).$$

Tu $\delta(X)$ označuje funkcijo δ v I-dimenzionalnem prostoru:

Here $\delta(X)$ denotes δ function in I-dimensional space:

$$\delta(X) = \prod_{I=1}^{I} \delta(x_I) \qquad (19).$$

Gostota robne funkcije porazdelitve verjetnosti v M-dimenzionalnem podprostoru je podana z:

$$f(G) = \int f(G \oplus H)dH = \frac{1}{N}\sum_{n=1}^{N}\delta(G - G_n) \quad (20).$$

Pri tem velja:

$$dG = dx_1\, dx_2 \ldots dx_M \quad (21),$$

$$G_n = (x_1, x_2, \ldots, x_M)_n \quad (22),$$

$$\delta(G) = \prod_{I=1}^{M}\delta(x_I) \quad (23).$$

Pogojna verjetnost je lahko sedaj formalno predstavljena z izrazom:

$$f(H|G) = \frac{\sum_{n=1}^{N}\delta(H - H_n)\,\delta(G - G_n)}{\sum_{n=1}^{N}\delta(G - G_n)} \quad (24).$$

Tega preprostega obrazca ne moremo uporabiti neposredno, ker se funkcija δ pojavi v imenovalcu. Zato sledimo Parzenovi metodi in aproksimiramo funkcijo δ z zvezno, regularno funkcijo [7]. Med različnimi možnimi aproksimacijami izberemo sferično Gaussovo funkcijo kot najprimernejšo za predstavitev porazdelitve gostote verjetnosti:

$$\delta_a(X) = \frac{1}{(2\pi)^{(I/2)}\,\sigma^I}\left[\frac{-\sum_{i=1}^{I} x_i^2}{2\sigma^2}\right] \quad (25).$$

Pri tem se pojavi problem izbire širine σ. Poglavitni namen vpeljevanja Gaussove funkcije je, da razširimo vpliv posamezne meritve v okolico vzorčnih vektorjev. Vendar pa razdalja med vzorci ni vnaprej znana. Če je S_x standardni odmik spremenljivke X, potem lahko priredimo porazdelitvi karakteristično prostornino S_x^I v I-dimenzionalnem prostoru. Če hočemo prostor pokriti z N območji širine σ, moramo izbrati $\sigma^I N = S_x^I$ ali:

$$\sigma = \frac{S_x}{N^{(1/I)}} \quad (26).$$

The density of the marginal probability distribution function in M-dimensional subspace is:

Where we define:

The conditional probability density function is then formally represented by the equation:

This simple formula cannot be applied without modification, because the δ function is in the denominator. We therefore follow the Parzen's approach [7] and substitute the δ function by a smooth, regular one. As the most appropriate for description of the probability distributions we choose the spherical Gaussian function:

A question about the value of the width σ appears here. The Gaussian function is introduced in order to spread the influence of a particular empirical point to its neighborhood. The distance between sample vectors is not known in advance, so we assign a characteristic volume S_x^I in I-dimensional sample space to the probability distribution. If we want to cover the distribution by N regions of the characteristic width σ, then we have to choose $\sigma^I N = S_x^I$ or:

Za veliko število I lahko poenostavimo $N^{(1/I)} = 1$ in $\sigma_n = S_x$. Pri tem mora biti standardni odmik S_x ocenjen s poprejšnjimi meritvami. Gostoto pogojne verjetnosti lahko nato opišemo z:

For large dimensionality I we can assume $N^{(1/I)} = 1$ and $\sigma_n = S_x$. The standard deviation S_x can be estimated from the data. The conditional probability density can be now expressed as:

$$f_a(H|G) = \frac{\sum_{n=1}^{N} \delta_a(H - H_n)\, \delta_a(G - G_n)}{\sum_{n=1}^{N} \delta_a(G - G_n)} \tag{27}$$

Če vstavimo to enačbo v izraz za optimalno cenilko $\hat{H}_0(G)$, dobimo preprost izraz:

If we put this expression into the equation for the estimator $\hat{H}_0(G)$ we get:

$$\hat{H}_0(G) = \sum_{n=1}^{N} C_n H_n \tag{28}$$

Pri tem je:

Here:

$$C_n = \frac{\delta_a(G - G_n)}{\sum_{n=1}^{N} \delta_a(G - G_n)} \tag{29}$$

Po prejšnji definicije je:

From the previous definition it follows:

$$\delta_a(G - G_n) = \frac{1}{(2\pi)^{(M/2)}\sigma^M} \left[\frac{-\|G - G_n\|^2}{2\sigma^2}\right] \tag{30}$$

$$\|G\|^2 = \sum_{I=1}^{M} x_I^2 \tag{31}$$

Karakteristično pri tej metodi je, da je optimalna cenilka izražena kot linearna kombinacija prototipnih vzorčnih vektorjev H_n. Koeficient C_n opisuje mero podobnosti med podanim vektorjem G in prototipnimi delnimi vektorji G_n. Za opis podobnosti je uporabna Evklidska razdalja $\|G - G_n\|$. Iz same definicije koeficienta C_n pa izhajata lastnosti:

It is characteristic of this method that the optimal estimator is described as a linear combination of prototype sample vectors H_n. The coefficients C_n represent a relative measure of similarity between the given vector G and the truncated prototype vectors G_n. The Euclidean distance $\|G - G_n\|$ describes the similarity. The coefficients C_n satisfy the conditions:

$$0 < C_n < 1 \quad \text{in} \quad \sum C_n = 1 \tag{32}$$

Privzemimo, da je podana množica vzorčnih točk $X_n = (G_n, H_n)$ in delni vektor G. Širina Gaussove funkcije označuje področja okrog vzorčnih točk. Nakazani problem ocene neznanega H iz danega G se prevede na določanje podobnosti med G in prototipnim G_n. Oblika cenilke H kaže, da prispevajo k oceni vrednosti H predvsem vzorčne točke, ki imajo delne vektorje G_n najbolj podobne

Let us now consider a set of the prototype vectors $X_n = (G_n, H_n)$ and a given partial vector G. Parameter σ denots a sphere around each sample point X_n. The problem of determining the unknown H from the given G is reduced to determination of the similarity between G and prototypes G_n. The definition of H shows that the prototypes X_n that have the vectors G_n most similar to the given vector G mostly contribute to the estimation of H.

vektorju G. V tem je glavna razlika med našo cenilko in običajno, linearno regresijo. V našem primeru opisujemo lastnosti lokalno s pomočjo vzorčnih točk, medtem ko pri običajni regresiji prilagodimo pojavu vrsto parametrov, ki globalno opisujejo obliko ustreznega, vnaprej privzetega zakona. Zaradi razlikovanja obeh primerov imenujemo našo metodo neparametrična regresija. Ustrezni sistem za obdelavo informacije ima strukturo nevronske mreže, v kateri prototipne vzorčne točke X_n opisujejo odzivne parametre nevronov [1], [4].

Neugodno pri tej metodi je, da uporaba cenilke $\hat{H}_0$ na prototipni vrednosti G_n ne vrne nujno vrednosti H_n, ampak dobimo oceno:

$$\hat{H}_0(G_n) = H_n + \varepsilon \qquad (33).$$

Lokalno napako cenilke in tudi ustrezni popravek opišemo z $\varepsilon = (H - H_n)$. Numerični primeri so pokazali, da dobimo boljše rezultate, če popravimo prototipno vrednost H_n v nasprotni smeri napake ε tako, da je popravljena vrednost:

$$H_n' \rightarrow H_n - \varepsilon = H_n + \left(H_n - H_0(G_n)\right) \qquad (34).$$

3 RAČUNALNIŠKO SIMULIRANJE PREIZKUŠANJA

Z namenom, da prikažemo opisano metodo, smo zasnovali dve vrsti eksperimenta. V prvi smo z računalniškim programom simulirali izvore *AE* na primerno izbranih mestih preizkusnega objekta. Iz časovnih zakasnitev med posameznimi signali, ki jih izračunamo analitično, in znanih koordinat izvora in lege zaznaval, smo izračunali prototipne vzorčne vektorje X_n in iz teh sestavili izkustveno bazo. Z uporabo te baze ter podanega testnega delnega vektorja časovnih zakasnitev, ki ga dobimo s simuliranjem izvora *AE* kjerkoli na objektu, lahko z opisano neparametrično regresijo določimo koordinate izvora. Prednost numeričnega preizkusa je v preprostem spreminjanju geometrijskih lastnosti vzorca in v izključitvi morebitnih motečih dejavnikov, kakršen je v primeru dejanskega preizkusa šum.

Uporabnost opisane metode smo ugotavljali s simuliranjem dveh skupin izvorov na podanem vzorcu. Prva je bila uporabljena za oblikovanje baze, druga pa za izračun napake ocenjevanja. V ta namen so bile uporabljene samo časovne zakasnitve pri simuliranem izvoru, iz njih pa ocenjene koordinate izvora z uporabo neparametrične regresije. Tako dobljene rezultate smo primerjali z vnaprej privzetimi koordinatami izvora in tako ugotavljali napako.

This property indicates the main difference between our and the most well known linear regression In our case, the properties of the relation between G and H are described locally by the sample points, while in linear regression we use a set of adaptable parameters that describe the properties of natural law globally. Due to this difference the method was named non-parametric regression. The corresponding information processing system exhibits the structure of an artificial neural network in which the prototypes X_n describe the response parameters of neurons [1], [4].

A weakness of our method is that the application of the estimator $\hat{H}_0$ on the prototype vector G_n does not necesarrily reproduce the expected vector H_n. Instead, we get the estimation:

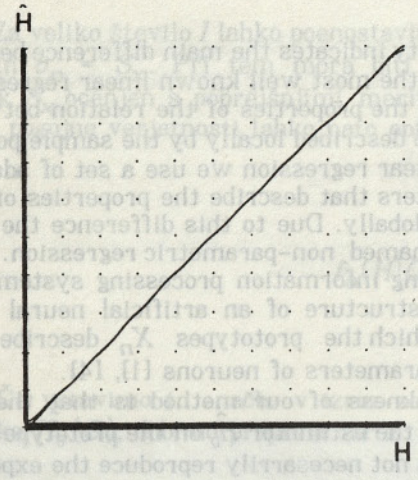
We describe the local estimaton error and also its correction by the discrepancy $\varepsilon = (H - H_n)$. Numerical examples have shown that the estimation error can be diminished by using prototypes shifted in the opposite direction to error ε:

3 COMPUTER SIMULATION OF EXPERIMENT

In order to demonstrate the applicability of the proposed method we prepared two kinds of experiments. In the first, numerical experiment, discrete *AE* events were simulated on the computer by calculating the time delays for a set of sources. From the calculated time delays and corresponding source coordinates, the set of prototype vectors X_n was formed and stored as a data base. With this data base and a new test partial vector comprised of time delays, the source coordinates were estimated. The advantage of this numerical experiment is in the simple variability of the sample geometry and the absence of experimental noise.

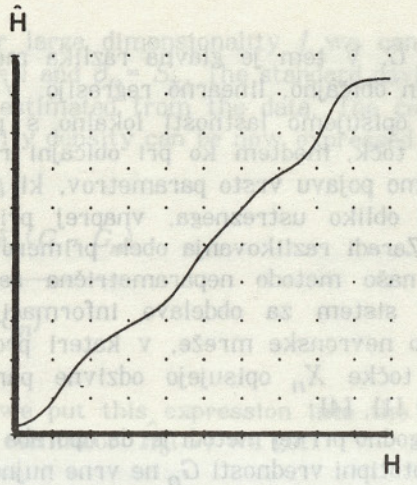
The performance of the method was estimated by simulating two sets of sources on various positions of the assumed sample. The first, training set was then used to form the data base while the second, test one, was applied to estimate the error of the estimation. For this purpose, only time delays of the simulated sources were applied in the estimation of the source coordinates by non-parametric regression. The estimated source coordinates were then compared with the true ones.

Figures 1 and 2 correspond to the simulated stick. They show the relation between the true and estimated position of the source for the case of uniform and random distribution of 10 prototype points along the stick. The test experiment was simulated by changing the position of the source from one to the other sensor along the sample.



Sl. 1. *Simuliranje linearnega problema*
H – dejanska lega izvora, $\hat{H}$ – ocenjena lega izvora
10 enakomerno razporejenih izvorov

Fig 1. *Simulation of the linear problem*
H – true source position, $\hat{H}$ – estimated source position
10 uniformly distributed prototypes applied



Sl. 2. *Simuliranje linearnega poblema*
H – dejanska lega izvora, $\hat{H}$ – ocenjena lega izvora
10 naključno razporejenih izvorov

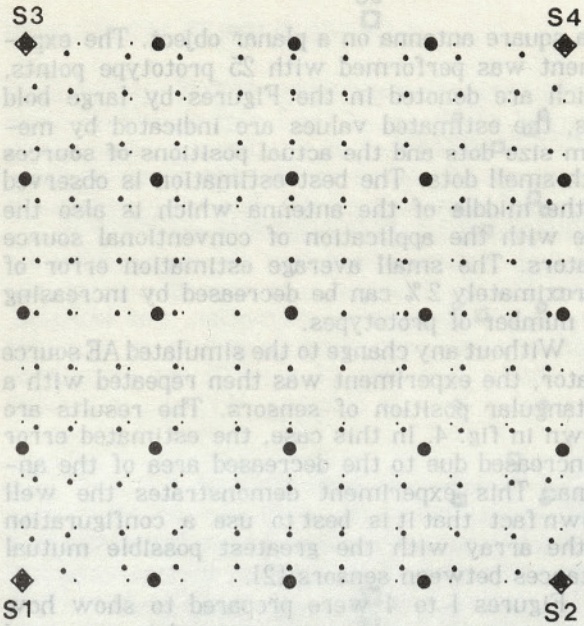
Fig. 2. *Simulation of the linear problem*
H – true source position, $\hat{H}$ – estimated source position
10 randomly distributed prototypes applied

Sliki 1 in 2 kažeta primer simuliranja na palici. Izkustvena baza je zgrajena v prvem primeru z enakomerno, v drugem pa z naključno razporejenimi izvori na palici, preverjanje metode pa je izvedeno na isti množici izvorov. Preizkus smo simulirali s spreminjanjem lege izvora *AE* od enega proti drugemu zaznavalu v zaporedju majhnih korakov. Dejanske lege izvorov so prikazane na abscisi, ocenjene lege pa na ordinati. Premica pod 45^0 bi ustrezala natančni določitvi lege izvora, vendar pa zaradi končnega števila prototipnih podatkov izračun ne da popolnoma točnih rezultatov. Diagrama kažeta, da dobimo pri enakomerni porazdelitvi prototipnih točk boljše rezultate kakor pri naključni. V primeru enakomerne porazdelitve metoda dobro deluje v srednjem delu palice, na obeh robovih pa pride do majhnega odstopanja. Vzrok za napako je v dejstvu, da ima robna testna točka vse prototipne točke na svoji levi ali desni strani, pri čemer vsi podobnostni koeficienti povzročajo premik ocenjene lege izvora proti sredini. To je sistematična napaka metode, ki jo je mogoče zmanjšati z uporabo eliptičnih Gaussovih funkcij. V primeru naključne porazdelitve prototipov neenakomernost njihove koncentracije povzroči tudi neenakomernost njihovih prispevkov k izračunani vrednosti. Položnejši odseki krivulje nakazujejo mesta, kjer je zbranih več prototipnih točk na majhnem območju, do strmega prehoda krivulje pa pride na mestih, kjer prototipnih točk ni. Napako lahko zmanjšamo z uporabo spremenljive širine σ, s čimer pa postane metoda bolj zapletena.

Slike 3 do 5 kažejo simulirane ravninske primere. Izkustvena baza je oblikovana na točkah pravokotne mreže znotraj območja, ki ga ograjujejo

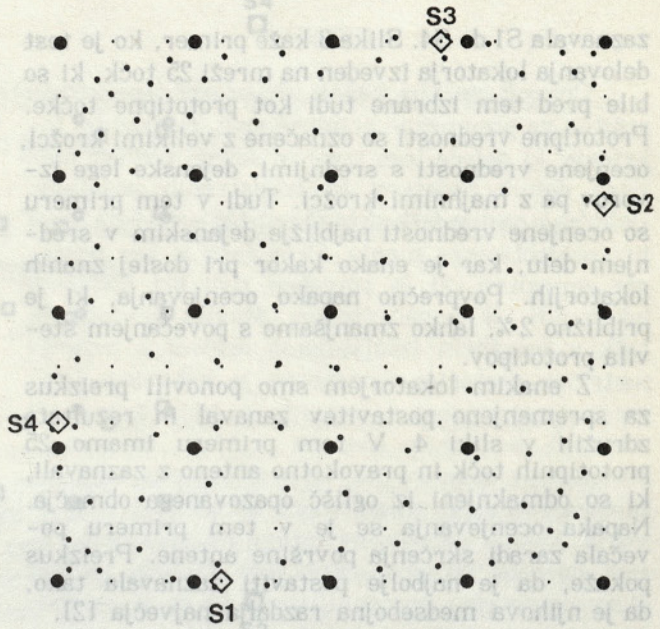
The true source position is shown horizontally while the estimated source position is shown vertically. A line inclined at 45^0 would correspond to the correct determination of source positions, but due to the finite number of prototype points, the estimation is not exact. The diagrams show that a uniform distribution of prototype points yields a better estimation of the true position than a random one. In the case of uniform distribution, the estimation is better in the middle of the stick, while at both ends a small discrepancy between the true and estimated positions is observable. This discrepancy can be explained as follows: when an AE source originates in the middle of a stick then the prototype points are distributed to the left and right side of it and their opposing contributions results in an approximately correct estimation of the true position. This is not the case when the source is placed near the end of the element where the prototype points all contribute to the estimated position in the same direction, which results in a shift of the estimated position towards the middle of the element. This systematic error can be reduced by increasing the number of prototype points or by utilizing elliptical Gaussian functions. In the case of random distribution of prototypes, the variability in their concentration also causes variability of the estimated source coordinate. The sections of lesser inclination of the curve indicate regions of increased density of prototype points while steep transitions correspond to regions with a low density of prototype points. This deficiency can be improved by introducing a variable width a of smoothing function which, however, increases the complexity of the numerical processing.

Figures 3 to 5 show the performance of non-parametric regression in the cases of planar location. Figure 3 shows the most simple exemple



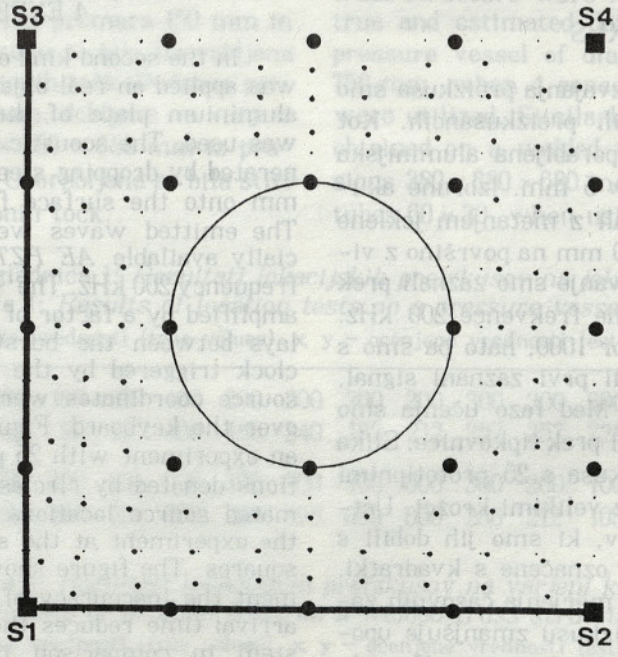
Sl. 3. *Simuliranje ravninskega problema s kvadratično anteno*
majhna točka – dejanska lega izvora, srednja točka – ocenjena lega izvora, velika točka – prototip, romb – lega zaznavala
25 enakomerno razporejenih prototipov

Fig. 3. *Simulation of planar location problem using square antenna*
small dot – true source position, medium dot – estimated source position, large dot – prototype, diamond – sensor position
25 equally spaced prototypes applied



Sl. 4 *Simuliranje ravninskega problema s pravokotno anteno*
majhna točka – dejanska lega izvora, srednja točka – ocenjena lega izvora, velika točka – prototip, romb – lega zaznavala
25 enakomerno razporejenih prototipov

Fig. 4. *Simulation of planar location problem using rectangular antenna*
small dot – true source position, medium dot – estimated source position, large dot – prototype, diamond – sensor position
25 equally spaced prototypes applied



Sl. 5. *Simuliranje ravninskega problema na preizkušancu z luknjo*
majhna točka – dejanska lega izvora, srednja točka – ocenjena lega izvora, velika točka – prototip, kvadratek – lega zaznavala; 24 enakomerno razporejenih prototipov

Fig. 5. *Simulation of planar location problem on a sample with a hole*
small dot – true source position, medium dot – estimated source position, large dot – prototype, square – sensor position 24 equally spaced prototypes applied

zaznavala S1 do S4. Slika 3 kaže primer, ko je test delovanja lokatorja izveden na mreži 25 točk, ki so bile pred tem izbrane tudi kot prototipne točke. Prototipne vrednosti so označene z velikimi krožci, ocenjene vrednosti s srednjimi, dejanske lege izvorov pa z majhnimi krožci. Tudi v tem primeru so ocenjene vrednosti najbližje dejanskim v srednjem delu, kar je enako kakor pri doslej znanih lokatorjih. Povprečno napako ocenjevanja, ki je približno 2 %, lahko zmanjšamo s povečanjem števila prototipov.

Z enakim lokatorjem smo ponovili preizkus za spremenjeno postavitev zanaval in rezultate združili v sliki 4. V tem primeru imamo 25 prototipnih točk in pravokotno anteno z zaznavali, ki so odmaknjeni iz oglišč opazovanega območja. Napaka ocenjevanja se je v tem primeru povečala zaradi skrčenja površine antene. Preizkus pokaže, da je najbolje postaviti zaznavala tako, da je njihova medsebojna razdalja največja [2].

Slike 1 do 4 prikazujejo, kako lahko neparametrična regresija zamenja sedanje lokatorje izvorov *AE*. Naslednji primer, prikazan na sliki 5, pa nas opozori že na nekatere prednosti nevronske mreže v primerjavi z običajnimi lokatorji. Nespremenjeni lokator iz prejšnjih primerov smo uporabili sedaj na ravninskem preizkušancu s krožno luknjo. Uporabili smo 24 prototipnih točk. Napaka med dejanskimi (majhne pike) in ocenjenimi legami (srednji krožci) je v povprečju manjša od 2%, kar navadno zadostuje za praktično uporabo.

4 PREIZKUS

V naslednjem koraku izvajanja preizkusa smo lokator uporabili na realnih preizkušancih. Kot prvi preizkušanec je bila uporabljena aluminijska plošča dimenzij 600 × 600 × 5 mm. Izbruhe akustične emisije smo generirali z metanjem jeklene kroglice s premerom Φ = 1,0 mm na površino z višine 10 mm. Emitirano valovanje smo zaznali prek zaznaval *AE PZT* resonančne frekvence 200 kHz. Signale smo ojačali za faktor 1000, nato pa smo s posebno uro, ki jo je sprožil prvi zaznani signal, merili časovne zakasnitve. Med fazo učenja smo koordinate izvora *AE* vnašali prek tipkovnice. Slika 6 prikazuje rezultate preizkusa s 25 prototipnimi izvori na legah, označenih z velikimi krožci. Ustrezne ocenjene lege izvorov, ki smo jih dobili s ponavljanjem preizkusa, so označene s kvadratki. Slika kaže, da nenatančnost merjenja časovnih zakasnitev pri dejanskem preizkusu zmanjšuje uporabnost naše metode v primerjavi z numerično simuliranimi primeri. Napaka se v realnem primeru pojavi dvakrat – prvič pri oblikovanju izkustvene baze in drugič pri izvajanju testa. Kljub temu pa je povprečna napaka ocenjevanja približno le 5%, kar je podobno kakor pri običajnih lokatorjih.

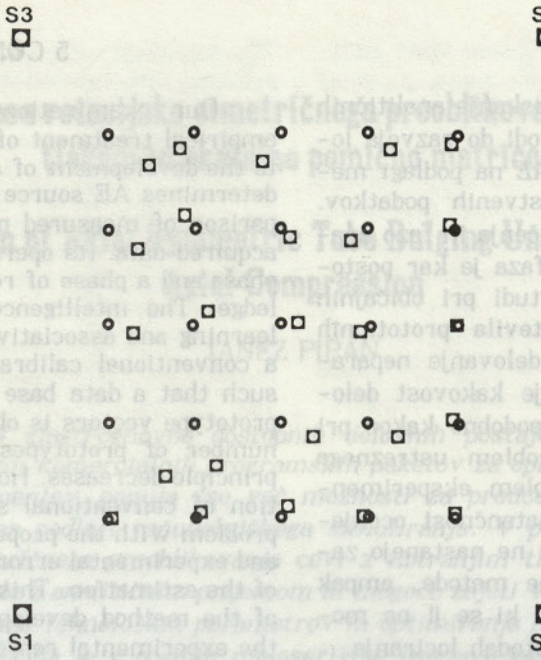
of a square antenna on a planar object. The experiment was performed with 25 prototype points, which are denoted in the Figures by large bold dots, the estimated values are indicated by medium size dots and the actual positions of sources with small dots. The best estimation is observed in the middle of the antenna which is also the case with the application of conventional source locators. The small average estimation error of approximately 2 % can be decreased by increasing the number of prototypes.

Without any change to the simulated AE source locator, the experiment was then repeated with a rectangular position of sensors. The results are shown in fig. 4. In this case, the estimated error is increased due to the decreased area of the antenna. This experiment demonstrates the well known fact that it is best to use a configuration of the array with the greatest possible mutual distances between sensors [2].

Figures 1 to 4 were prepared to show how our system can replace conventional locators and corresponding analytical treatment, while the next two examples are used to demonstrate the advantage of our system. Without any change, our system is now applied to source location on a planar sample with a circular hole. In this case, the basic information is provided by 24 prototypes, again presented on Figure 5 by large bold dots. The discrepancy between the true (thin points) and estimated (bold dots) source position is on average lesser than 2 %, which is usually sufficient for practical location purposes.

4 EXPERIMENT

In the second kind of examination, the method was applied on real objects. As a first sample, an aluminium plate of dimensions 600×600×5 mm was used. The acoustic emission bursts were generated by dropping steel balls of diameter Φ = 1.0 mm onto the surface from a height of 10 mm. The emitted waves were detected by commercially available *AE PZT* transducers of resonant frequency 200 kHz. The detected signals were amplified by a factor of 1000 before the time delays between the bursts were determined in a clock triggered by the first arriving burst. The source coordinates were supplied to the system over the keyboard. Figure 6 shows the result of an experiment with 25 prototype sources at positions denoted by circles. The corresponding estimated source locations obtained by repetition of the experiment at the same point are denoted by squares. The figure shows that in a true experiment the inaccuracy of the determination of the arrival time reduces the performance of our system in comparison to numerically simulated examples. The error is introduced into the experimental procedure twice: first, in the detection of the prototype data and second, during the execution of the test. In spite of the problem, the average estimation erorr is about 5%, which is approximately the same as observed with conventional locators.



Sl. 6. *Eksperimentalni rezultati ravninske lokacije z uporabo pravokotne antene*
krožec – prototipni izvor, kvadratek – eksperimentalno dobljena lega izvora,
večji kvadratek – lega zaznavala
25 enakomerno razporejenih prototipov

Fig. 6. *Experimental results of planar location using rectangular antenna*
circles – prototype sources, squares – experimentally estimated source position,
large square – sensor position
25 equally spaced prototypes applied

Poleg opisanih preizkusov sta bila izvedena tudi preizkusa na majhni jeklenki in na varjeni konstrukciji. Preglednica 1 kaže dejanske in ocenjene lege izvorov na jeklenki premera 150 mm in dolžine 750 mm. Pri preizkusu so bila uporabljena štiri zaznavala in 16 prototipnih točk. Podobno prikazuje preglednica 2 rezultate, dobljene na varjeni konstrukciji dimenzij 380 × 380 × 680 mm iz pravokotnih cevi 60 × 30 mm. Uporabljena so bila štiri zaznavala in deset prototipnih točk.

In adddition to the experiment on the planar samples, tests on a small pressure vessel and a truss structure were made. Table I presents the true and estimated data for the case of a steel pressure vessel of diameter 150 mm and length 750 mm, when 4 sensors and 16 prototype points were utilized. Similarly, Table II shows the data obtained on a welded truss structure of dimensions 380 × 380 × 680 mm and cross section of side tubes 60 × 30, when using 10 prototype points.

Preglednica 1: *Rezultati lokacijskih preizkusov na jeklenki*
Table 1: *Results of location tests on a pressure vessel*
x, y – dejanske vrednosti (true values), x, y – ocenjene vrednosti (estimated values)

x	100	100	100	100	200	200	200	200	300	300	300	300
$\hat{x}$	110	99	112	100	185	240	192	212	257	257	228	221
y	300	200	100	000	300	200	100	000	300	200	100	000
$\hat{y}$	296	196	101	000	290	198	089	000	286	212	105	002

Preglednica 2: *Rezultati lokacijskih preizkusov na varjeni konstrukciji*
Table 2: *Results of location tests on a welded truss structure*
x, y – dejanske vrednosti (true values), x, y – ocenjene vrednosti (estimated values)

x	100	200	100	200	400	400	600	700	600	700
$\hat{x}$	142	201	107	159	389	429	604	667	581	699
y	000	000	200	200	000	200	000	000	200	200
$\hat{y}$	068	001	199	172	002	175	009	019	196	200

5 SKLEP

Opisani izsledki kažejo, da iskanje analitičnih rešitev za posamezne primere vodi do razvoja lokatorja, ki določa lege izvorov *AE* na podlagi meritev delnih podatkov in izkustvenih podatkov. Delovanje je razdeljeno v fazo učenja in fazo analize pridobljenega znanja. Prva faza je kar postopek umeritve, ki je potreben tudi pri običajnih lokatorjih. S povečevanjem števila prototipnih točk v splošnem izboljšujemo delovanje neparametrične regresije, vendar pa je kakovost delovanja omejena, saj se pojavita podobno kakor pri običajnih lokatorjih tudi tu problem ustreznega simuliranja izvorov AE in problem eksperimentalnega šuma, ki zmanjšujeta natančnost ocenjevanja. Vendar pa opisane težave ne nastanejo zaradi uporabe izbrane izkustvene metode, ampak eksperimentalne neponovljivosti, ki se ji ne moremo izogniti tudi pri drugih metodah lociranja.

Bistvene prednosti opisane izkustvene metode v primerjavi z običajnimi lokatorji izhajajo iz dejstva, da pri zamenjavi strukture mreže zaznaval, ki sestavljajo anteno AE, ne potrebujemo dodatnega programiranja. To pomeni, da je isti lokator zelo prilagodljiv in uporaben za različne postavitve. Celo spreminjanje števila zaznaval v mreži je preprosto in zahteva le spremembo števila komponent, uporabljenih za opis podatkovnega vektorja.

Za opisani sistem je značilno, da lahko z njim rešujemo tudi direkten problem. Lega je v tem primeru znana, ocenjevanje pa se nanaša na časovne zakasnitve.

5 CONCLUSION

Our examination shows that an entirely empirical treatment of the location problem leads to the development of an intelligent locator which determines AE source coordinates based on comparison of measured partial data with previously acquired data. Its operation consists of a learning phase and a phase of recall of the acquired knowledge. The intelligence is a consequence of the learning and associative estimation. For learning, a conventional calibration procedure is extended such that a data base of a sufficient number of prototype vectors is obtained. With an increasing number of prototypes, the estimation error in principle decreases. However, as with the calibration of conventional source locators, there is a problem with the proper simulation of AE sources and experimental error that diminish the accuracy of the estimation. This is not an inherent problem of the method developed but of difficulties with the experimental reproducibility of the phenomenon, which cannot be avoided even in the application of other methods.

The greatest advantage of the empirical approach stems from the fact that no additional treatment of the phenomenon and corresponding programming is needed when the structure of the sensory network that forms the AE antenna is changed. The same locator is thus very flexible and applicable in different configurations. Even the variation of the number of sensors needs no more than a new setting of the number of components used in the description of the data vector.

It is characteristic for the presented method that forward problems can be solved by it as well. In this case the location is given and the time delays are estimated.

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